Final Project Report

A Multidimensional Analysis of Willingness to Share Rides in a Future of Autonomous Vehicles

Prepared for **Teaching Old Models New Tricks (TOMNET) Transportation Center**

By

Irfan Batur
Email: ibatur@asu.edu

Ram M. Pendyala
Email: ram.pendyala.@asu.edu

Tassio B. Magassy
Email: tmagassy@asu.edu

School of Sustainable Engineering and the Built Environment
Arizona State University
660 S. College Avenue, Tempe, AZ 85287-3005

September, 2023

TECHNICAL REPORT DOCUMENTATION PAGE

16. Abstract

A sustainable transportation future is one in which people eschew personal car ownership in favor of using automated vehicle (AV) based ridehailing services in a shared mode. However, the traveling public has historically shown a disinclination towards sharing rides and carpooling with strangers. In a future of AV-based ridehailing services, it will be necessary for people to embrace both AVs as well as true ridesharing to fully realize the benefits of automated and shared mobility technologies. This study investigates the factors influencing the willingness to use AV-based ridehailing services in the future in a shared (with strangers) mode. This is done through the estimation of a comprehensive behavioral model system on a comprehensive survey data set that includes rich information about attitudes, perceptions, and preferences regarding the adoption of automated vehicles and shared mobility modes. Model results show that current ridehailing experiences strongly influence the likelihood of being willing to ride AV-based services in a shared mode. Campaigns that provide opportunities for individuals to experience such services firsthand would potentially go a long way in enabling a shared mobility future at scale. In addition, a number of attitudinal variables are found to strongly influence the adoption of future mobility services; these findings provide insights on likely early adopters of shared automated mobility services and the types of educational awareness campaigns that may effect change in the prospects for such services.

TABLE OF CONTENTS

`

LIST OF TABLES

LIST OF FIGURES

EXECUTIVE SUMMARY

A sustainable transportation future is one in which people eschew personal car ownership in favor of using automated vehicle (AV) based ridehailing services in a shared mode. However, the traveling public has historically shown a disinclination towards sharing rides and carpooling with strangers. In a future of AV-based ridehailing services, it will be necessary for people to embrace both AVs as well as true ridesharing to fully realize the benefits of automated and shared mobility technologies. This study investigates the factors influencing the willingness to use AV-based ridehailing services in the future in a shared (with strangers) mode. This is done through the estimation of a comprehensive behavioral model system on a comprehensive survey data set that includes rich information about attitudes, perceptions, and preferences regarding the adoption of automated vehicles and shared mobility modes. Model results show that current ridehailing experiences strongly influence the likelihood of being willing to ride AV-based services in a shared mode. Campaigns that provide opportunities for individuals to experience such services firsthand would potentially go a long way in enabling a shared mobility future at scale. In addition, a number of attitudinal variables are found to strongly influence the adoption of future mobility services; these findings provide insights on likely early adopters of shared automated mobility services and the types of educational awareness campaigns that may effect change in the prospects for such services.

INTRODUCTION

The transportation ecosystem has experienced a few key disruptions in the recent past. After several decades of little to no innovation and game changing technologies, the world of transportation has seen the emergence of new mobility options and technology disruptors within the span of 15 years. A key development in the transportation space is the rise of ridehailing services, also referred to as mobility-on-demand (MOD) services or mobility-as-a-service (MaaS), which enable individuals to summon a curb-to-curb ride using a convenient mobile application that integrates trip/vehicle tracking and payment. Ridehailing services have grown rapidly in the past decade and are now offered in cities and countries around the world; companies that offer such services include Lyft in the US, Uber in many different countries, Didi in China, and Ola in India (along with several other Australasian nations). Ridehailing services now serve millions of trips worldwide on a daily basis. In a few markets, ridehailing services have introduced true rideshare services where complete strangers ride together in the same vehicle; such shared rides come at a lower cost, but a longer travel and wait time due to the circuity imposed by sharing. Due to the complexity of ride matching and the reluctance of consumers to accept a travel time penalty in exchange for lower cost, the rideshare feature has been implemented in only select markets (Malik et al., 2021). Many believe ridehailing services exhibit the potential to reduce private vehicle ownership, as individuals increasingly embrace a service-based transportation system (thus reducing the need to rely on privately owned cars).

At the same time, rapid advances are being made in transportation automation with the development of automated vehicles offering the promise for driverless transport in the future. In fact, such driverless rides are now being offered in a couple of markets (McAslan et al., 2021), ushering in a whole new era of mobility. The impediment to widespread adoption of ridehailing services is that the fare is rather prohibitive for regular/daily use of such services (Henao et al., 2019). If, however, the driver is removed from the equation, then the price of such services may potentially drop significantly (Gurumurthy et al., 2019; Hyland and Mahmassani, 2020), although there is some continued uncertainty of the extent to which fares could drop even in an automated vehicle-based ridehailing service future (Irannezhad and Mahadevan, 2022). Because of the potential game changing nature of automated vehicle technology, many have touted a utopian future vision of transportation characterized by shared automated vehicles (SAV) providing mobility-as-a-service at scale roaming around the streets of a city, providing low-cost on-demand shared rides. If the vehicles are electric, that would further advance a utopian transportation future in which vehicular travel leaves behind a much smaller operational carbon footprint. And if the vehicles are connected, enabling vehicle-to-vehicle and vehicle-to-infrastructure communication, additional efficiencies can be gained in a future of automated, connected, electric, shared (ACES) vehicles providing rides on-demand.

The utopian vision of a safe, sustainable, affordable, and automated transportation future will only be realized only if people *share* rides in large numbers. Although travel demand may decrease in a scenario where individuals pay by the trip, substantial gains (in terms of reduced number of vehicle trips) can only happen if people are willing to, and actually do, share rides on a consistent basis. However, the history of ridesharing in the United States is not particularly encouraging. Average vehicle occupancies have continuously decreased over time in the US and carpool mode share has exhibited a consistent decline over the past several decades, despite many efforts to promote carpooling through the construction of high occupancy vehicle (HOV) lanes, managed lanes, and rideshare programs and incentives (Olsson et al., 2019). With millions of driverless automated vehicles available to service rides on-demand, shared rides could potentially

be offered with minimal inconvenience at low cost. In such an automated vehicle service future, to what extent would individuals be willing to *share* rides with strangers? Who would be early adopters of such *shared* automated vehicle services, and who would be reluctant to participate in such a mobility future? Does current experience with private or shared ridehailing services affect the willingness to share rides in an automated vehicle future? These are the questions that this study seeks to answer through a rigorous behavioral modeling exercise. It is envisaged that insights to these questions will help in the identification and recruitment of early adopters; these early successes can then be marketed and communicated to the reluctant market segments with a view to influence their attitudes and perceptions and bring them on-board as well. If current experience with private or shared ridehailing services has a positive effect on willingness to share rides in an automated vehicle future, then efforts and campaigns may be directed towards enabling individuals to gain such experiences in the current ecosystem.

The literature dedicated to understanding willingness to share in an automated vehicle mobility-as-a-service future is rather limited. There is a vast body of literature that has examined the adoption of ridehailing services and the characteristics of those who are more or less likely to use such services (Dias et al., 2017). In general, it is found that younger age, highly educated, technology-savvy, urban dwellers are more likely to embrace ridehailing services. A number of studies have also explored the willingness of individuals to adopt and ride in automated vehicles. Studies have explored factors affecting willingness to ride alone (Lavieri et al., 2017) and in a shared modality (Stopher et al., 2021; Gurumurthy et al., 2019; Hyland and Mahmassani, 2020). In general, it is found adopters of shared automated vehicle services would include low income individuals (Sener and Zmud, 2019), and those with higher levels of education (Gurumurthy and Kockelman, 2020). Although these studies present excellent insights, there is very limited knowledge of the role of current ridehailing experience in shaping willingness to ride automated vehicles in the future in different modalities (alone, with friends and family, or with strangers). In addition, even if a prior study purported to study this particular linkage, the influence of attitudinal factors was rarely incorporated.

This study involves the specification and estimation of a simultaneous equations model system in which current ridehailing experience and future willingness to share rides in an autonomous vehicle future are modeled jointly. The model is estimated on a data set derived from a detailed survey conducted in 2019 in four automobile-oriented metropolitan areas in the United States, namely, Phoenix, Austin, Atlanta, and Tampa. The survey includes detailed information about current ridehailing experience and stated willingness to ride in automated vehicles in alternative configurations in the future (ride alone, ride with family and friends, ride with strangers). The model system includes a number of latent attitudinal constructs to account for their influence in shaping mobility choices and willingness to share rides with strangers. A host of socio-economic and demographic variables serve as exogenous explanatory variables. The entire model system is estimated in a single step through the use of the Generalized Heterogenous Data Model (GHDM) methodology developed by Bhat (2015).

The remainder of the report is organized as follows. The next section presents a detailed description of the data and the endogenous variables of interest. The third section presents the modeling framework and methodology, and the fourth section that presents detailed model estimation results. Finally, the fifth section offers a discussion of the study implications and concluding thoughts.

DATA DESCRIPTION

This section presents an overview of the survey data set used in this study. First, an overview of the survey and the sample description is provided, and second, deeper insights on the endogenous variables and attitudinal indicators used in the modeling effort are furnished.

Survey Data

The data set used in this study is derived from a comprehensive survey conducted in 2019 in four automobile-oriented metropolitan areas in the US, namely, Phoenix (Arizona), Austin (Texas), Atlanta (Georgia), and Tampa (Florida). The survey was specifically aimed at gathering very detailed information about attitudes and perceptions towards emerging transportation technologies such as ridehailing services, micromobility technologies, and autonomous vehicles. The survey also gathered detailed socio-economic, demographic, and mobility behavior data so that the responses of individuals to questions about ridehailing services and automated vehicles could be placed in appropriate context. Full details about the survey instrument, questions/content, sampling strategies, response rates, and weighting methods are documented in Khoeini et al. (2021).

A total of 3,465 responses were collected. After removing records with missing data and filtering obviously erroneous records, the clean data set included 3,377 respondents. All respondents are adults (18+ years of age) residing in the specific four metropolitan areas of the United States. Table 1 provides an overview of the sample characteristics. It is found that there is a slightly larger share of females (at 57 percent), and a somewhat larger share of young (18-30 years) individuals in the respondent sample. Only 6.6 percent of respondents report not having a driver's license. Just over one-half of the sample is employed with 26.8 percent of the respondents indicating that they are neither a worker nor a student. Educational attainment distribution shows that the sample is fairly well-educated overall, with 36.5 percent having a Bachelor's degree and 24.5 percent having a graduate degree. Just over seventy percent of the respondents are White and 7.6 percent are Black. The income distribution shows that 34 percent fall in the middle household income range of $50,000 to $99,999 per year. The sample shows a good variation across the different income groups. About 40 percent of the respondents reside in households with three or more members, 70 percent reside in a stand-alone home, and 68 percent own the home in which they reside. Vehicle ownership profile shows that only four percent reside in households with no vehicles, which is not surprising given the very automobile-oriented nature of the transportation systems in the four metropolitan areas where data was collected. A smaller percent of respondents (just 7.6 percent) are based in Tampa, with the remainder of the sample quite evenly spread across the other three metro areas.

Table 1 Sample Socio-economic and Demographic Characteristics

Individual Characteristics (N = 3,377)		Household Characteristics (N = 3,377)	
Variable	%	Variable	%
Gender		**Household annual income**	
Female	56.9	Less than $25,000	10.7
Male	43.1	$25,000 to $49,999	15.8
Age category		$50,000 to $99,999	34.1
18-30 years	26.0	$100,000 to $149,999	21.0
31-40 years	11.4	$150,000 to $249,999	12.4
41-50 years	14.9	$250,000 or more	6.0
51-60 years	16.7	**Household size**	
61-70 years	16.1	One	21.2
71+ years	14.9	Two	38.7
Driver's license possesion		Three or more	40.1
Yes	93.4	**Housing unit type**	
No	6.6	Stand-alone home	70.2
Employment status		Condo/apartment	20.6
A student (part-time or full-time)	10.1	Other	9.3
A worker (part-time or full-time)	52.1	**Home ownership**	
Both a worker and a student	11.0	Own	68.0
Neither a worker nor a student	26.8	Rent	26.0
Education attainment		Other	6.0
Completed high school or less	9.3	**Vehicle ownership**	
Some college or technical school	29.7	Zero	3.9
Bachelor's degree(s) or some grad. school	36.5	One	24.0
Completed graduate degree(s)	24.5	Two	39.9
Race		Three or more	32.2
Asian or Pacific Islander	8.8	**Location**	
Black or African American	7.6	Atlanta, GA	29.6
Native American	0.5	Austin, TX	32.1
White or Caucasian	71.0	Phoenix, AZ	30.7
Other	12.2	Tampa, FL	7.6
Endogenous Variables	%		%
Willingness to Use AV Ridehailing Service: Private (Alone or Family/Friends)		**Willingness to Use AV Ridehailing Service: Pooled with Strangers**	
Strongly disagree	18.4	Strongly disagree	30.7
Somewhat disagree	11.7	Somewhat disagree	27.5
Neutral	22.1	Neutral	21.4
Somewhat agree	34.9	Somewhat agree	16.4
Strongly agree	12.9	Strongly agree	4.0

Endogenous Variables and Attitudinal Indicators

This study aims to understand user willingness to ride in a future automated vehicle (AV) based ridehailing service in different modes – *private mode* (riding alone or with friends and family) and *shared mode* (riding with strangers). The survey included questions asking respondents to indicate the degree to which they agree that they are willing to ride in AV-based ridehailing services (in the future) in each of these modes (bottom of Table 1). As expected, individuals are more agreeable to riding in an AV-based ridehailing service in a private mode, either alone or with friends and family.

The objective of this study is to examine the potential influence of experiences with using *current* ridehailing services on the degree to which individuals are willing to use *future* AV-based ridehailing services in a private or shared mode. Respondents were asked to indicate the frequency with which they currently use ridehailing services. Although pooled ridehailing services (such as

UberPool and LyftShare) are not offered in all four metropolitan area markets, these services are available in select markets. Based on the responses to current ridehailing experience questions, respondents were grouped into three categories:

o   No experience: if a respondent has not used (or is unfamiliar with) *both* private and pooled ridehailing service options;
o   Private ridehailing experience only: if a participant has used private ridehailing services (ride alone or with friends and family only) but has no experience with the shared option; and
o   Pooled (shared) experience: if a participant reported using shared ridehailing services, involving strangers as fellow passengers (note that individuals in this group may have also used ridehailing services in a private mode).

   As expected, among individuals who fall into the third group (experienced shared ridehailing services), the vast majority of respondents have also experienced private ridehailing services. Figure 1 depicts the bivariate relationship between the intention to use AV ridehailing services in the future and current ridehailing experience.
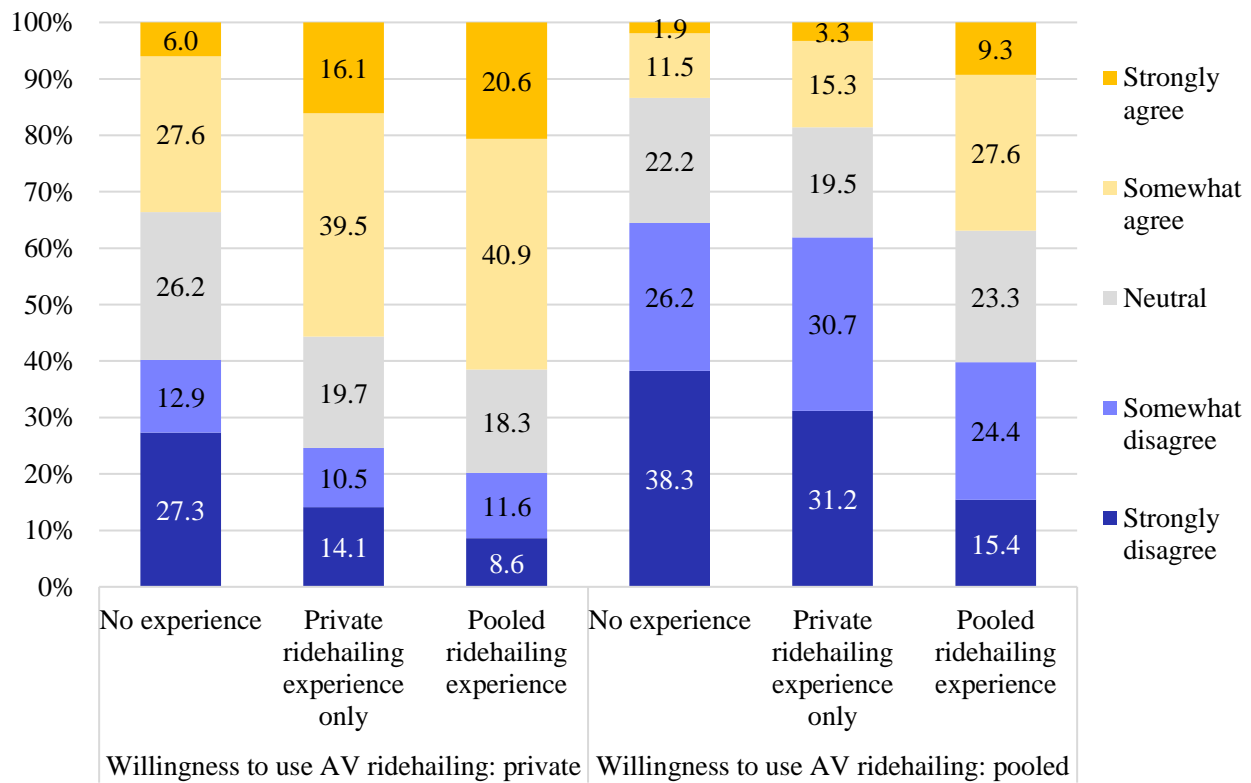
Figure 1 Willingness to Use AV Ridehailing Services by Current Ridehailing Experience (N= 3,377)

   The bivariate chart depicts a discernible pattern, suggesting that there is an association between current experience with using ridehailing services and the future intentions of using AV-based services in different modes. The percent that is not inclined to use AV-based ridehailing services in the future declines as the current experience with ridehailing services is richer. In

general, the graphic shows that the percent willing to ride privately in AV-based ridehailing services exceeds the percent willing to *share* rides with *strangers* in an AV-based ridehailing future. This bivariate relationship and the overall socio-economic profile of the sample renders the data set suitable for the type of modeling effort undertaken in this study.

An important set of determinants of the adoption of new technologies and mobility options is attitudes, values, perceptions, and preferences. These traits are often not captured in survey data sets, and simply assumed to be part of the unobserved random error term in statistical and econometric choice models. To overcome this limitation and capture the relationship between current and future ridehailing service use more accurately, this study incorporates the influence of attitudinal variables within the overall modeling exercise. The survey included a large number of attitudinal statements, many of which are correlated with one another; these statements were intended to elicit information about the degree to which individuals embrace new technologies, are environmentally oriented, enjoy social interactions, and would like to reside in urban environments of different types (besides a host of other attitudes related to lifestyle and mobility preferences). Based on an extensive review of the literature, a series of trials of alternative model specifications, and behavioral intuitiveness considerations, three attitudinal constructs are specified and utilized in this study. They may be termed as *AV Technology Trust*, *Discomfort Around Strangers*, and *Transit-oriented Lifestyle*. These three constructs are chosen because the willingness to ride in an AV is likely influenced by the level of trust that individuals place in such technology, the willingness to share is likely influenced by the level of comfort that individuals feel being around strangers, and the propensity to use shared modes of transportation is likely influenced by the degree to which an individual prefers a transit-oriented mobility lifestyle.

Three attitudinal indicators were used to define each of the latent constructs. Figure 2 shows the latent factors and the respective attitudinal statement indicators that define them. For each attitudinal statement, the figure shows the distribution of responses ranging from *strongly disagree* to *strongly agree*. The distributions are intuitive and consistent with expectations. For the sake of brevity and given that the distributions and latent constructs are largely self-explanatory, an in-depth description of the latent constructs is suppressed.
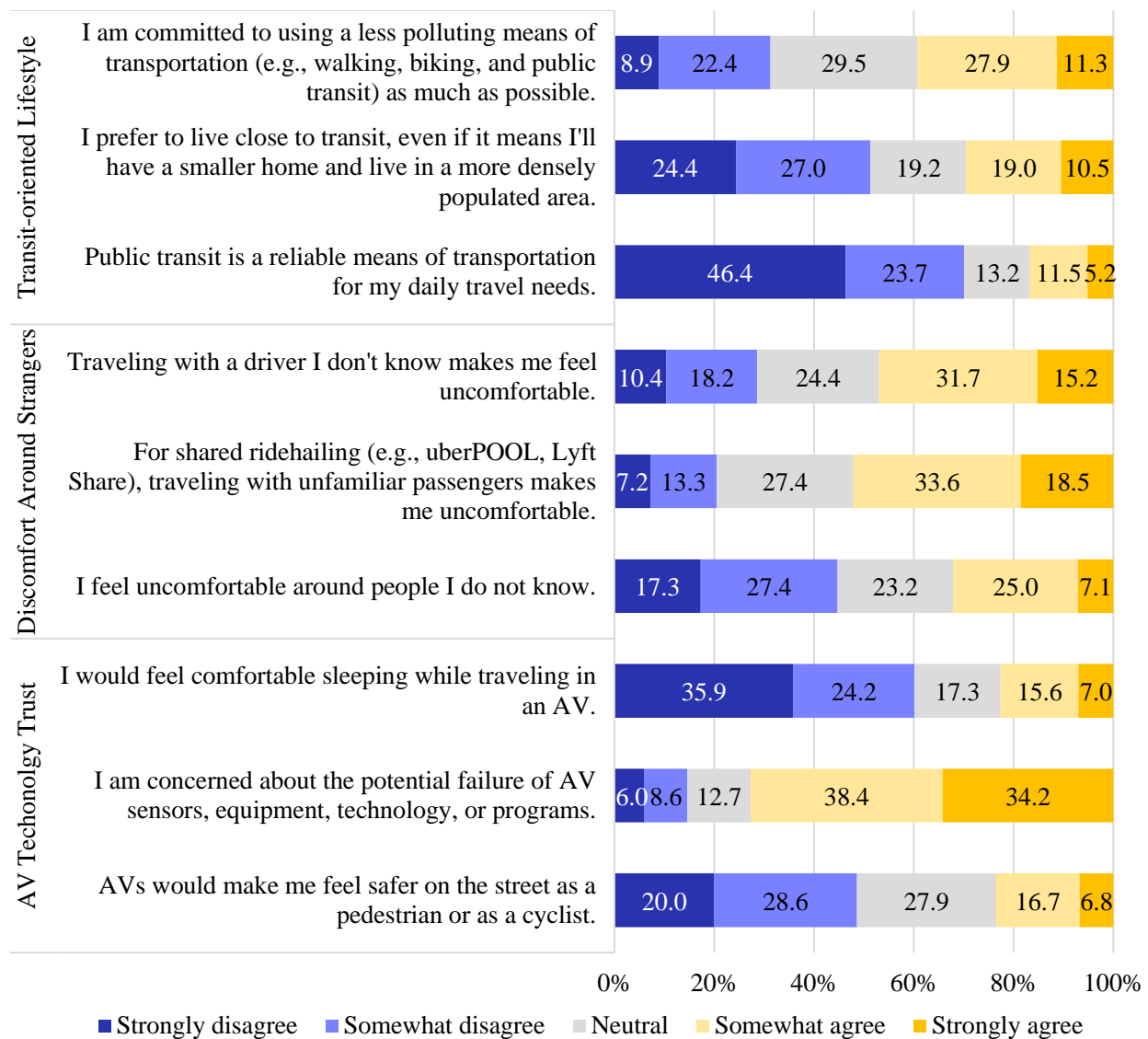
Figure 2 Distribution of Attitudinal Indicators of Latent Constructs (N= 3,377)

MODELING FRAMEWORK

This section presents a brief overview of the model structure and formulation. In the interest of brevity, only a qualitative description of the modeling methodology is provided in this manuscript. A detailed exposition of the model formulation and estimation methodology is provided elsewhere [1] and is not critical for understanding the empirical results presented later. The formulation is quite long and notation-intensive, and interested readers should refer to Bhat (2015) for details.

Model Structure

This section presents the behavioral modeling framework adopted in this study. A simplified representation of the model structure is shown in Figure 3. The model system is intended to connect

---

[1] https://journals.sagepub.com/doi/full/10.1177/03611981231201111

two key endogenous variables, namely, the *current ridehailing experience* and the future *intent to use AV-based ridehailing services in different modes* (private versus shared). Thus, the right hand side of the figure shows the dependent variables with current ridehailing experience influencing the willingness to ride future AV-based ridehailing services in a private or shared mode. It is hypothesized that current ridehailing experience would play a role in shaping people's willingness to ride in future AV-based services, and the bivariate relationship depicted in Figure 1 supports this hypothesis. A host of socio-economic, demographic, household, and other travel and built environment attributes are treated as exogenous variables. They are assumed to influence both the latent constructs as well as the main outcomes (endogenous variables). The three latent constructs serve as mediating variables; they are both influenced by the exogenous variables, and in turn, they influence the main outcome variables of interest. Correlations between the attitudinal constructs are accommodated to reflect the possible presence of correlated unobserved factors simultaneously affecting multiple behavioral measures and latent attitudinal variables. This is possible because the latent attitudinal constructs are treated as stochastic variables with a random error term. Because error correlations between the latent constructs are explicitly accommodated in the model formulation, it is not necessary to separately specify error correlations between the main outcome variables. The error correlations between the latent constructs engender error correlations between the main outcome variables by virtue of the joint model specification in which all parameters and relationships are estimated simultaneously in a single step using the Generalized Heterogeneous Data Model (GHDM) methodology (Bhat, 2015). Thus, the model structure accounts for endogeneity, the stochastic nature of latent constructs, and error correlations between latent constructs and between the main endogenous variables of interest. Further details about the error structures may be found in Bhat (2015).
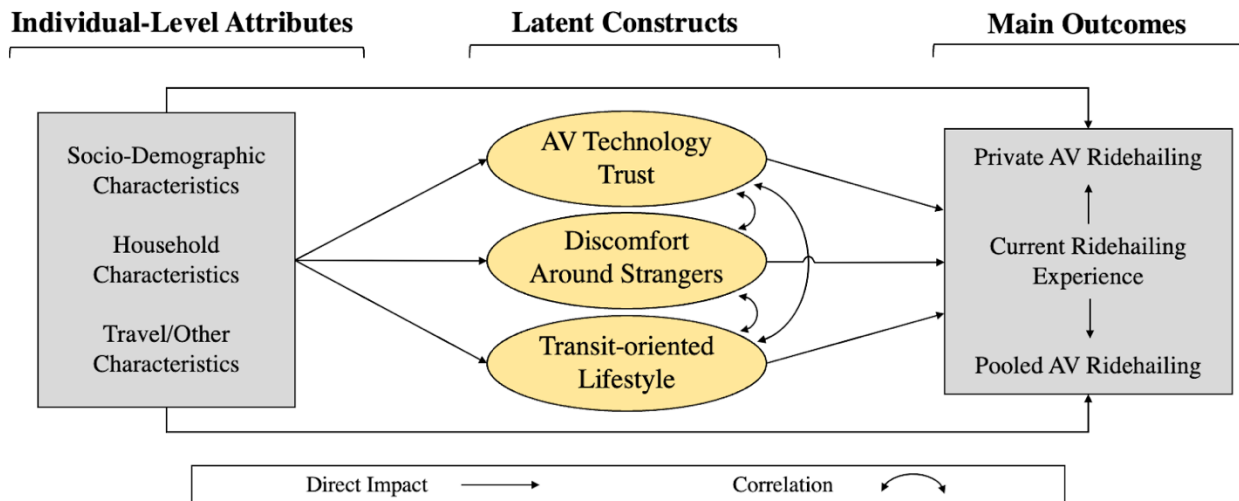
Figure 3 Model Structure and Behavioral Framework

Modeling Methodology
The modeling methodology adopted in this study is a special case of the Generalized Heterogeneous Data Model (GHDM) developed by Bhat (2015). The model is adapted to accommodate one multinomial (nominal) choice variable (corresponding to current ridehailing experience) and two ordinal choice variables (corresponding to degree of willingness to ride in an AV-based ridehailing service in the future in a private or shared mode). The private AV-ridehailing and shared AV-ridehailing measures constitute two ordinal dependent variables that are influenced

by the nominal choice variable of current ridehailing experience. A direct relationship between the outcome variables may be incorporated because of the behaviorally intuitive and logical nature of the influence. As mentioned earlier, unobserved stochastic psychosocial constructs serve as latent factors that provide a structure to the dependence among the endogenous variables of interest, while the latent constructs themselves are explained by exogenous variables and may be correlated with one another in a structural relationship.

There are two components to the latent factors component of the GHDM model. The first is the latent variable structural equation model (SEM) and the second is the measurement equation model (MEM) relating latent factors to their attitudinal measures. The SEM component defines stochastic latent constructs as a function of exogenous variables and unobserved error components that may be correlated with one another. The joint model of endogenous outcomes captures the influence of latent factors and socio-economic variables on the dependent variables of interest. No separate error correlations are estimated because the error terms of the SEM equations (which define the latent variables) permeate into the endogenous choice model component (which describes the outcome variables), resulting in an efficient and compact dependence structure among all endogenous variables. The error terms are assumed to be drawn from multivariate normal distributions (with the dimension equivalent to the number of latent variables).

The formulation depends on the types of dependent variables comprising the model, following the usual ordered response formulation with standard normal error terms for the ordinal indicator variables, and the typical random utility-maximization model with a probit kernel for the nominal and ordinal outcomes of primary interest. The latent constructs are estimated at the person level (as a stochastic function of individual socio-economic attributes). These latent constructs influence the current ridehailing experience endogenous variable in a cross-sectional setting (one observation per respondent) as well as both AV ridehailing interest (private and pooled) endogenous variables. In doing so, the model structure simultaneously captures not only unobserved factors impacting the indicator and endogenous outcomes of interest, but also accounts for covariations among the three endogenous variables of the same individual. Thus, the stochastic latent factors help to efficiently incorporate observed and unobserved individual heterogeneity in variables of interest through interactions of the latent factors with exogenous variables. The GHDM was estimated according to methods described in Bhat (2015) and Bhat (2018).

MODEL ESTIMATION RESULTS
Detailed model estimation results are furnished in this section. As the GHDM comprises two components, they are presented and discussed in sequence.

Latent Construct Model Components
The results for the latent construct model component are presented in Table 2. The table has two parts to it. The first part shows the influence of various exogenous variables on the three latent constructs. The second part shows the factor loadings of latent variables on the various attitudinal indicators that define them. The top half of the table shows that the latent attitudinal constructs are influenced by a host of socio-economic and demographic variables.

Table 2 Determinants of Latent Variables and Loadings on Indicators (N= 3,377)

| | Latent construct model | | | | | |
| Explanatory variables (base category) | AV technology trust | | Discomfort around strangers | | Transit-oriented lifestyle | |
	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
Age (*)						
18-40 years	0.28	7.26	na	na	0.30	5.43
65 years or older	na	na	0.13	2.78	na	na
Gender (male)						
Female	-0.46	-12.81	0.44	12.19	na	na
Race (not Black or African American)						
Black or African American	-0.26	-3.76	na	na	na	na
Employment (*)						
Worker	na	na	-0.14	-3.67	na	na
Student	na	na	na	na	0.59	8.53
Both worker and student	0.16	2.66	na	na	na	na
Education (less than Bachelor's degree)						
Bachelor's or graduate degree	na	na	-0.12	-3.28	0.16	3.46
Household structure (not in a nuclear family)						
Nuclear family	na	na	na	na	-0.15	-2.73
Household annual income (*)						
Less than $50,000	na	na	na	na	0.30	5.76
$100,000 or more	0.16	4.59	–	–	na	na
Correlations between latent constructs						
AV technology trust	1.00	na	-0.27	-8.32	0.21	4.44
Discomfort around strangers	na	na	1.00	na	-0.18	-3.32
Transit-oriented lifestyle	na	na	na	na	1.00	na

Attitudinal indicators	Loadings of latent variables on indicators (measurement equation model component)					
AVs would make me feel safer on the street as a pedestrian or as a cyclist.	0.97	50.62	na	na	na	na
I am concerned about the potential failure of AV sensors, equipment, technology, or programs.	-1.15	-55.64	na	na	na	na
would feel comfortable sleeping while traveling in an AV.	1.25	58.46	na	na	na	na
I feel uncomfortable around people I do not know.	na	na	0.29	15.95	na	na
For shared ridehailing (e.g., uberPOOL, Lyft Share), traveling with unfamiliar passengers makes me uncomfortable.	na	na	1.09	27.76	na	na
Traveling with a driver I don't know makes me feel uncomfortable.	na	na	1.61	18.41	na	na
Public transit is a reliable means of transportation for my daily travel needs.	na	na	na	na	0.66	27.55
I prefer to live close to transit, even if it means I'll have a smaller home and live in a more densely populated area.	na	na	na	na	0.51	21.72
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	0.28	13.56

Note: Coef = coefficient; "–" = not statistically significantly different from zero at the 90% level of confidence; "na" = not applicable; *Base category is all other complementary categories for the corresponding variable.

As expected, younger individuals depict a higher level of trust in technology and embrace a transit-oriented lifestyle more than older age groups; these findings are consistent with expectations and prior literature (Hulse et al., 2018; Nielsen et al., 2018). Older individuals are less comfortable around strangers, reflecting a more cautious attitude that comes with age. Females

trust technology less and are more uncomfortable around strangers due to privacy and security concerns (also reported by Sener et al., 2019). Blacks depict a lower trust in AV technology, presumably due to the digital divide, as documented in the literature that Blacks and other minority groups do not enjoy the same level of technology access as majority groups (Wu et al., 2021). Students are more likely to embrace a transit-oriented lifestyle (consistent with expectations and findings reported by Brown et al., 2016), while individuals who are both workers and students trust AV technology more so than others. This is likely a reflection of the greater exposure to technology experienced by individuals who are both workers and students. Households that constitute a nuclear family are less likely to be transit-oriented; households with children likely reside in lower density suburban neighborhoods and are therefore more car-oriented than other types of households that may reside in urban contexts (Magassy et al., 2022). Lower income individuals are more transit-oriented while high-income individuals depict a higher level of trust in AV technology. The error correlations show a negative relationship between AV technology trust and discomfort around strangers. This makes sense in that unobserved factors that enhance AV technology trust (e.g., like to be more adventurous and risk-taking) are likely to contribute to lower discomfort of being around strangers. On the other hand, there is a positive error correlation between AV technology trust and transit-oriented lifestyle, while there is a negative correlation between discomfort around strangers and transit-oriented lifestyle. Those who value privacy (uncomfortable around strangers) are likely to eschew a transit-oriented lifestyle in favor of an automobile-oriented lifestyle. These findings are consistent with expectations, justifying the adoption of a joint simultaneous equations model.

The bottom half of the table shows the equivalent of factor loadings of latent variables on the attitudinal indicators. AV technology trust is positively associated with feeling safe on the streets with AVs present and feeling comfortable sleeping in an AV, but negatively associated with concern about potential technology failure. These are behaviorally intuitive and statistically significant loadings. For discomfort around strangers, all three loadings are positive; the attitudinal statements correspond to indicators that measure the degree of discomfort around unknown people, discomfort traveling with unfamiliar passengers, and discomfort traveling with a driver who is not known, and hence the positive loadings are behaviorally intuitive. Finally, the transit-oriented lifestyle construct is associated positively with attitudinal indicators measuring the extent to which individuals feel that public transit is a reliable means of travel, prefer living close to transit even at the expense of home size, and are committed to using less polluting means of transportation. Once again, all loadings have behaviorally intuitive signs and are statistically significant. These three latent constructs are used in the measurement equation model component to explain the relationship between current ridehailing experience and willingness to ride in a future AV-based ridehailing service in a private or shared mode.

Bivariate Model of Behavioral Outcomes
Table 3 presents estimation results for the measurement equation model component. This component corresponds to the behavioral outcomes of interest, namely ridehailing experience and and willingness to use future AV-based ridehailing services in a private (alone or with friends/family) and shared/pooled (with strangers) mode.

Table 3 Estimation Results of the Joint Model of Intentions to Use AV Ridehailing Services and Current Ridehailing Experience (N= 3,377)

| Explanatory variables (base category) | Current ridehailing experience (base: no experience) | | | | Private AV ridehailing (ordered, 5-level) | | Pooled AV ridehailing (ordered, 5-level) | |
| | Private only experience | | Pooled experience | | | | | |
	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
Current ridehailing experience (no experience)								
Private only experience	na	na	na	na	0.49	11.23	na	na
Pooled experience	na	na	na	na	0.63	11.15	0.60	10.14
Latent constructs								
AV technology trust	na	na	na	na	0.85	44.39	0.58	29.75
Discomfort around strangers	-0.32	-13.29	-0.42	-12.42	na	na	-0.33	-16.99
Transit-oriented lifestyle	na	na	0.94	24.86	na	na	0.16	6.37
Age (*)								
18-30 years	0.43	6.41	na	na	na	na	na	na
31-40 years	0.45	6.59	na	na	na	na	na	na
51-60 years	na	na	na	na	-0.22	-4.04	na	na
65 years or older	na	na	-0.29	-3.10	-0.34	-6.87	na	na
Gender (male)								
Female	0.28	5.71	0.25	3.75	0.10	2.53	na	na
Race (*)								
White	0.24	4.68	na	na	na	na	na	na
Non-Hispanic White	na	na	na	na	0.20	3.46	na	na
Asian or Pacific Islander	na	na	0.48	5.35	na	na	na	na
Employment (*)								
Worker	0.31	6.03	0.49	6.39	na	na	na	na
Student	na	na	-0.37	-4.07	na	na	na	na
Education (less than Bachelor's degree)								
Bachelor's or graduate degree	0.36	6.89	0.28	3.96	0.19	4.79	na	na
Household size (*)								
1	na	na	0.21	2.92	na	na	na	na
2	na	na	na	na	na	na	-0.16	-4.14
Vehicles available in household (zero)								
1 or more	na	na	-0.91	-7.67	na	na	na	na
Household annual income (*)								
$50,000 to $99,999	na	na	na	na	na	na	0.09	2.38
$100,000 or more	0.61	11.74	0.69	9.84	na	na	na	na
Online shopping (no online deliveries in last month)								
At least one online delivery in last month	na	na	na	na	0.42	6.67	0.21	2.95

Table 3 Estimation Results of the Joint Model of Intentions to Use AV Ridehailing Services and Current Ridehailing Experience (N= 3,377) (continued)

	Main outcome variables							
	Current ridehailing experience (base: no experience)				Private AV ridehailing (ordered, 5-level)		Pooled AV ridehailing (ordered, 5-level)	
	Private only experience		Pooled experience					
Explanatory variables (base category)	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
Location (*)								
Atlanta, GA	na	na	na	na	–	–	na	na
Austin, TX	0.10	1.82	0.63	8.30	na	na	na	na
Phoenix, AZ	na	na	na	na	0.14	2.75	0.16	3.71
Commute distance (*)								
Between 20-40 miles	na	na	na	na	na	na	–	–
Population density (high population density area)								
Low population density area (< 2900 persons/sq. mi.)	-0.21	-4.41	-0.27	-4.31	na	na	na	na
Constant	-1.07	-13.81	-1.20	-7.19	na	na	na	na
Thresholds								
1|2	na	na	na	na	-0.53	-6.32	0.33	3.96
2|3	na	na	na	na	0.01	0.10	-0.63	-7.70
3|4	na	na	na	na	0.82	10.08	-1.46	-17.40
4|5	na	na	na	na	2.33	26.85	-2.72	-28.33

Correlations	Private only experience	Pooled experience	Private AV ridehailing	Pooled AV ridehailing
Private only experience	1.00	0.44	0.05	0.12
Pooled experience	na	1.00	0.14	0.28
Private AV ridehailing	na	na	1.00	0.36
Pooled AV ridehailing	na	na	na	1.00

Data fit measures	GHDM	Independent model
Log-likelihood at convergence	-12090.58	-3710.01
Log-likelihood at constants		-13842.57
Number of parameters	116	79
Likelihood ratio test	0.127	0.103
Avg. prob. of correct prediction	0.039	0.035

Note: Coef = coefficient; "–" = not statistically significantly different from zero at the 90% level of confidence; "na" = not applicable; *Base category is all other complementary categories for the correspondent variable.

The key findings of interest are related to the endogenous variable and latent construct effects. It can be seen that the current ridehailing experience has a significant impact on the willingness to use AV-based ridehailing services in the future. Individuals having only a private ridehailing experience thus far (currently) are, as expected, more likely to be willing to engage in private AV-based ridehailing services in the future. However they are *not* more likely to engage in shared AV-based ridehailing services. On the other hand, individuals who have experienced pooled ridehailing services (currently) are more likely to be willing to ride future AV-based ridehailing services in *both* a private mode and a shared mode. In other words, people need to have the experience of shared rides (for themselves) to overcome the hesitation to ride future AV-based services with strangers. This is a key finding that has important implications for the types of strategies that need to be deployed to enhance a shared mobility future.

Latent attitudinal factors also play a key role in shaping the endogenous outcomes of interest. As expected, AV technology trust positively influences the willingness to ride AVs in a

private or shared mode. Those who are uncomfortable around strangers are less likely to use current ridehailing services (either in a private or pooled mode), which is not surprising, given that even riding privately in current ridehailing services entails being in the same vehicle with an unknown driver. Likewise, discomfort around strangers negatively influences the likelihood of being willing to ride future AV-based services in a shared mode. A transit-oriented lifestyle proclivity is, however, associated with a greater likelihood of being willing to ride future AV-based ridehailing services in a shared mode, presumably because such individuals are more open to using shared modes of transportation where fellow passengers are strangers. This is another set of key findings that has important implications for the types of awareness campaigns and messaging that is needed to overcome attitudinal barriers to adoption of a shared mobility future.

The rest of the table shows exogenous variable effects and a detailed exposition is not offered here in the interest of brevity. In general, it is found that young individuals are more likely to embrace ridehailing while older adults are less likely to do so, similar to those reported in the literature. Interestingly, age has no significant direct effect on willingness to ride AV-services in a shared/pooled mode; however, the indirect effects are mediated through the latent constructs. Although females trust technology less and are more uncomfortable around strangers (Table 2), they are more likely to use ridehailing services currently and future AV-based services in a private mode. As women have more complex travel patterns and may have lower access to a private vehicle, it is likely that they take advantage of the flexibility and convenience of ridehailing services despite issues related to technology trust and discomfort with strangers (Wu et al., 2021). Racial differences are found, with Asians more likely to use shared ridehailing services currently and Whites expressing a greater willingness to use future AV-based ridehailing services in a private mode. As expected, employment and education are both positively influencing ridesharing mode usage, but have no direct effect on willingness to ride future AVs in a shared mode. Single adults are more likely to use pooled ridehailing services currently, while individuals in two-person households are less likely to embrace a future shared AV-ride service; the underlying reasons for this latter finding are not clear and warrant further investigation.

Middle income individuals are more likely to embrace pooled AV ridehailing services, while those in the higher income group are more likely to be current users of ridehailing services. Individuals in the middle income age group are likely to be comfortable using technology and have a desire to enjoy cost savings that come with sharing rides in an AV future. Those who engage in more online shopping (essentially more prone to using technology for fulfilling activities) are more likely to embrace technology in the future; they are more likely to ride AV-based services in the future in both private and shared modes (although the coefficient for the *shared* option is only about one-half of the coefficient for the *private* option). Residents of Austin exhibit a greater proclivity towards using ridehailing services currently (in both private and pooled mode), which is consistent with the high-tech nature of the metropolitan area. On the other hand, residents of Phoenix express a greater likelihood of being willing to try future AV-based ridehailing services in both a private and shared mode. This is likely due to the familiarity with AV technologies that Phoenix residents enjoy, stemming from the current availability of AV-based ridehailing services in the metropolitan area (and people are able to see and experience AVs firsthand). Residents of low population density areas are less likely to use ridehailing services, presumably because such residents have access to their own private automobiles (Zhang and Zhang, 2018).

STUDY IMPLICATIONS AND CONCLUSIONS

The utopian vision of a sustainable mobility future is often described as one in which automated, connected, electric, and shared (ACES) vehicles serve the mobility needs of the public. While considerable strides are being made on the technological front to advance automated, connected, and electric vehicles, the transportation ecosystem continues to struggle with advancing a *shared* mobility paradigm – one in which *strangers* share the same vehicle at the same time to travel between origin and destination pairs that are reasonably aligned with one another. Past trends suggest that it is challenging to get people to share rides, as evidenced by the decline in carpool mode shares and average vehicle occupancies over the past several decades.

In an effort to better understand the factors that influence the willingness to share rides in an automated vehicle (AV)-based future, this study presents a behavioral choice model of the willingness to ride in future AV-based ridehailing services in a *private* or *shared* mode. The private mode entails riding in such vehicles alone or with friends and family, while the shared mode entails riding with strangers. The model estimation utilizes a comprehensive survey data set that includes detailed information about attitudes and perceptions towards automated vehicles and ridehailing services, and willingness to ride future AV-based services in private and shared modes. The model is a comprehensive econometric model system that accounts for the influence of current ridehailing experience on the willingness to ride AVs in the future in different modes, which is also treated as an endogenous variable in the model formulation. The model structure incorporates a battery of attitudinal statements represented by three latent attitudinal constructs (capturing lifestyle and mobility preferences) along with the usual host of exogenous socio-economic and demographic variables that typically influence mobility choices. The data set comprises more than 3,000 adults drawn from the Phoenix, Atlanta, Austin, and Tampa areas of the United States.

The model estimation results show that current ridehailing experiences (whether an individual has experienced private or pooled ridehailing services that currently exist in the market) significantly influence the likelihood of being willing to ride in AV-based services in the future. However, the model results suggest that mere *private* ridehailing experiences are not sufficient to bring about a higher proclivity towards embracing *shared* AV-based ridehailing services in the future. On the other hand, experience riding current ridehailing services in a pooled mode does significantly enhance the likelihood of being willing to ride future AV-based services in a *shared* mode. The bottom line is that experience matters; no amount of literature, brochures, publicity campaigns, and media coverage can overcome the barriers and hesitation to sharing rides with strangers. Whether it be the discomfort of being in close proximity of strangers, the inconvenience of increased wait and travel time due to trip circuity, or a desire for privacy, there are numerous barriers to widespread adoption of AV-based ridehailing services in a shared/pooled mode. To overcome these barriers, people need to experience such services firsthand, and become comfortable with the logistics and social aspects of a shared ride with a stranger. With traditional transit under threat in a post-COVID era, public transit agencies may be able to play a key role in advancing and implementing such flexible shared ride services, as has been done recently (De La Canal, 2022). This also speaks to the need to reimagine future automated vehicle designs, where individual passengers enjoy greater privacy, security, and comfort without feeling that other passengers are intruding in their personal space.

This is not to say that educational awareness campaigns, demonstrations, and media coverage are not useful. In fact, in this study, residents of Pheonix indicate a higher proclivity towards embracing an AV-based mobility future in *both* private and shared modes. This finding is very likely due to the rather significant presence of AVs and AV-based ridehailing services in the

Phoenix metropolitan area. The presence of such services engenders a sense of familiarity and comfort with the technology, that in turn advance a greater degree of willingness to embrace the technology. The study results show that attitudes, perceptions, and preferences strongly influence the willingness to ride AVs in different modalities. Trust in technology is critical as it positively impacts the proclivity to ride AVs in *both* modes. However, discomfort with strangers remains a barrier. Educational awareness campaigns should be aimed at making public aware of the reliability and performance of the technology to enhance trust in such automated vehicle systems. Unfortunately, media coverage tends to highlight technology failures, thus raising questions about the trustworthiness of these systems. Public and private entities should band together to provide accurate information about technology performance and safety, conduct demonstrations and trials, and run educational awareness campaigns. In addition, public and private entities involved in providing mobility services should continue to put appropriate safety systems in place to help individuals overcome discomfort with strangers. It may be necessary to provide special incentives to motivate individuals to try shared AV-based ridehailing services to accelerate the pace of adoption and convert the unwilling to the willing. The results provide key insights into likely early adopters of such shared AV-based ridehailing services (young, middle income, technology savvy individuals); start with these market segments, demonstrate and achieve success, and then other population subgroups are likely to follow as (negative) attitudes and perceptions are overcome.

REFERENCES

Bhat, C.R., A New Generalized Heterogeneous Data Model (GHDM) to Jointly Model Mixed Types of Dependent Variables. *Transportation Research B.* 2015. 79:50-77.

Bhat, C.R., New Matrix-Based Methods for the Analytic Evaluation of the Multivariate Cumulative Normal Distribution Function. *Transportation Research B,* 2018. 109:238-256.

Brown, A.E., Blumenberg, E., Taylor, B.D., Ralph, K., and Turley Voulgaris, C. A Taste For Transit? Analyzing Public Transit Use Trends Among Youth. *Journal of Public Transportation*, 2016. *19*:4.

De La Canal, N. This small city ditched its buses. Its public Uber-like service has been a big hit. https://www.npr.org/2022/07/19/1111765630/on-demand-shuttles-have-replaced-buses-in-a-small-north-carolina-town. 2022. Accessed August 2022.

Dias, F.F., Lavieri, P.S., Garikapati, V.M., Astroza, S., Pendyala, R.M., and Bhat, C.R. A Behavioral Choice Model of the Use of Car-Sharing and Ride-Sourcing Services. *Transportation*, 2017. *44*(6):1307-1323.

Gurumurthy, K.M., Kockelman, K.M., and Simoni, M.D. Benefits And Costs of Ride-Sharing in Shared Automated Vehicles Across Austin, Texas: Opportunities for Congestion Pricing. *Transportation Research Record*, 2019. *2673*(6):548-556.

Gurumurthy, K.M., and Kockelman, K.M. Modeling Americans' Autonomous Vehicle Preferences: A Focus on Dynamic Ride-Sharing, Privacy & Long-Distance Mode Choices. *Technological Forecasting and Social Change*, 2020, 150:119792.

Henao, A., and Marshall, W.E. The Impact of Ride Hailing on Parking (and Vice Versa). *Journal of Transport and Land Use*, 2019. *12*(1):127-147.

Hulse, L.M., Xie, H., and Galea, E.R. Perceptions of Autonomous Vehicles: Relationships with Road Users, Risk, Gender and Age. *Safety Science*, 2018. *102*:1-13.

Hyland, M., and Mahmassani, H.S. Operational benefits and challenges of shared-ride automated mobility-on-demand services. *Transportation Research Part A*, 2020.251-270.

Irannezhad, E., and Mahadevan, R. Examining Factors Influencing the Adoption of Solo, Pooling and Autonomous Ride-hailing Services in Australia. *Transportation Research C,* 2022. *136*:103524.

Lavieri, P.S., Garikapati, V.M., Bhat, C.R., Pendyala, R.M., Astroza, S., and Dias, F.F. Modeling Individual Preferences for Ownership and Sharing of Autonomous Vehicle Technologies. *Transportation Research Record*, 2017. *2665*(1):1-10.

Khoeini, S., Pendyala, R.M., Salon, D., Circella, G., Mokhtarian, P.L., Bhat, C.R., Maness, M., Mennon, N., Capasso da Silva, D., Batur, I., Dias, F., Kang, S., Lee, Y. TOMNET Transformative Transportation Technologies (T4) Survey. https://tomnet-utc.engineering.asu.edu/t4-survey/. Accessed August 2022.

Magassy, T.B., Batur, I., Mondal, A., Asmussen, K.E., Khoeini, S., Pendyala, R.M., and Bhat, C.R. Influence of Mode Use on Level of Satisfaction with Daily Travel Routine: A Focus on Automobile Driving in the United States. *Transportation Research Record*, 2022. 03611981221088199.

Malik, J., Alemi, F., and Circella, G. Exploring the Factors that Affect the Frequency of Use of Ridehailing and the Adoption of Shared Ridehailing in California. *Transportation Research Record*, 2021. *2675*(5):120-135.

McAslan, D., Najar Arevalo, F., King, D.A., and Miller, T.R. Pilot Project Purgatory? Assessing Automated Vehicle Pilot Projects in US Cities. *Humanities and Social Sciences Communications*, 2021. *8*(1):1-16.

Nielsen, T.A.S., and Haustein, S. On Sceptics and Enthusiasts: What are the Expectations Towards Self-driving Cars?. *Transport Policy*, 2018. *66*:49-55.

Olsson, L.E., Maier, R., and Friman, M. Why Do They Ride With Others? Meta-Analysis of Factors Influencing Travelers to Carpool. *Sustainability*, 2019. 11(8):2414.

Sener, I. N., Zmud, J., and Williams, T. Measures of Baseline Intent to Use Automated Vehicles: A Case Study of Texas Cities. *Transportation Research F*, 2019. *62*:66-77.

Stopher, P., Magassy, T.B., Pendyala, R.M., McAslan, D., Arevalo, F.N., and Miller, T. An Evaluation of the Valley Metro–Waymo Automated Vehicle RideChoice Mobility on Demand Demonstration. *Technical Report*. United States Department of Transportation. Federal Transit Administration. 2021.

Wu, X., Cao, J., and Douma, F. The Impacts of Vehicle Automation on Transport-disadvantaged People. *Transportation Research Interdisciplinary Perspectives*, 2021. *11*:100447.

Zhang, Y., and Zhang, Y. (2018). Examining the Relationship Between Household Vehicle Ownership and Ridesharing Behaviors in the United States. *Sustainability*, 2018. *10*(8):2720.