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

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Abstract

A sustainable transportation future is one in which people eschew personal car ownership in favor of using autonomous vehicle (AV)-based ridehailing services in a shared mode. However, the traveling public has historically shown a disinclination toward 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 investigated the factors influencing willingness to use AV-based ridehailing services in the future in a shared mode (i.e., with strangers). This was done through the estimation of a behavioral model system on a comprehensive survey data set that included rich information about attitudes, perceptions, and preferences pertaining to the adoption of AVs and shared mobility modes. The model results showed that current ridehailing experiences strongly influenced 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 to enabling a shared mobility future at scale. In addition, several attitudinal variables were found to strongly influence the adoption of future mobility services; these findings provide insights on the likely early adopters of shared autonomous mobility services and the types of educational awareness campaigns that may effect change in the prospects of such services.

Keywords

vehicle-highway automation, self-driving, autonomous vehicles, ridesharing, user experience, mobility-as-a-service, willingness to pool

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 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 United States, Uber in many different countries, Didi in China, and Ola in India (along with several other Australasian and African nations). Ridehailing services now serve millions of trips worldwide on a daily basis. In a few markets, ridehailing services have introduced true rideshare services in which

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complete strangers ride together in the same vehicle; such shared rides come at a lower cost, but a longer travel and wait time owing to the circuity imposed by sharing. Because of 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 (*1*). Many believe ridehailing services exhibit the potential to reduce private vehicle ownership (*2*, *3*), 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 autonomous vehicles (AVs) offering the promise of driverless transport in the future (*4*, *5*). In fact, such driverless rides are now being offered in a couple of markets (*6*, *7*), 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 (*8*). If, however, the driver is removed from the equation, then the price of such services may potentially drop significantly (*9–11*), although there is some continued uncertainty about the extent to which fares could drop even in an AV-based ridehailing service future (*12*). Because of the potential game-changing nature of automated vehicle technology, many have touted a utopian future vision of transportation characterized by shared autonomous vehicles (SAVs) providing MaaS at scale, roaming 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 would 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 (*13*, *14*). Although travel demand may decrease in a scenario in which individuals pay by the trip, substantial gains (e.g., a 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 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 lanes, managed lanes, and rideshare programs and incentives (*15*). 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 AV service future, to what extent would individuals be willing to share rides with strangers? Who would be the early adopters of such SAV 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 AV future? These are the questions that this study sought to answer through a rigorous behavioral modeling exercise. It was envisaged that insights into these questions would help in the identification and recruitment of early adopters; these early successes could then be publicized and communicated to the reluctant market segments with a view to influencing their attitudes and perceptions and bringing them on board as well. If an individual's current experience with private or shared ridehailing services has a positive effect on their willingness to share rides in an AV future, then efforts and campaigns might be directed toward enabling individuals to gain such experiences in the current ecosystem.

Literature dedicated to understanding the willingness to share rides in an AV MaaS future is quite limited (*16*, *17*). 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 (*18*). In general, younger, highly educated, technology-savvy, urban dwellers are more likely to embrace ridehailing services. Several studies have also explored the willingness of individuals to adopt and ride in AVs. Studies have explored the factors affecting willingness to ride alone (*19*) and in a shared modality (*9*, *10*, *20*). In general, adopters of SAV services would include low-income individuals (*21*) and those with higher levels of education (*17*). Although these studies present excellent insights, there is very limited knowledge of the role of current ridehailing experiences in shaping willingness to ride AVs in the future in different modalities (e.g., alone, with friends and family, or with strangers). Moreover, even if a prior study purported to have investigated this particular linkage, the influence of attitudinal factors was rarely incorporated.

One exception is a study by Lavieri and Bhat, which considered the influence of attitudinal factors in examining the relationship between current ridehailing experiences and future intentions to use shared/private ridehailing services for commute and leisure trips (*16*). The study was based on survey data collected from commuters in Dallas, TX, and employed a stated choice experiment to elicit information about mode choice intentions. This experiment involved presenting respondents with AV-based ridehailing options for hypothetical trips that varied in time, cost, and other factors, and asking them to choose between solo and pooled options. Given the experiment's focus on individual trips, the study incorporated attitudinal factors that might have the most significant influence on shaping decisions in this context, including privacy sensitivity, time sensitivity, and interest in the productive use of travel time. However, notwithstanding its valuable contributions to the body of literature and its similarity to this study, the Lavieri and Bhat study is limited in several ways (*16*). Their study focuses on hypothetical individual trips with varying trip characteristics, and therefore the findings may not necessarily indicate broader proclivities toward willingness to use AV-based ridehailing services, whether in private or shared mode. Furthermore, the selected attitudinal constructs are different in that they largely reflect trip-specific attributes and considerations. Thus, they do not capture the broader and more general attitudes, personality traits, and lifestyle preferences of the respondents, which may be critical to developing policies and incentives that promote use of shared AV mobility services. Finally, the findings of the study are less generalizable or transferable since it is based on a sample of commuters exclusively from Dallas, TX, whereas the sample used in this study was drawn from four different metropolitan regions in the United States, spanning the entire breadth of the country.

The current study further explores how current experiences with ridehailing services influence people's willingness to ride in AV-based ridehailing services in the future, by addressing the challenges and limitations identified in previous research. It involves the specification and estimation of a simultaneous equations model system in which current ridehailing experience and future willingness to share rides in an AV 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, AZ, Austin, TX, Atlanta, GA, and Tampa, FL offering a nuanced understanding of the potential geographic disparities that may affect the phenomena under investigation. The respondent sample includes individuals aged 18 years and above, thereby enabling inferences to be drawn about population subgroups. The survey includes detailed information about current ridehailing experience and stated willingness to ride in AVs in alternative configurations in the future (ride alone, ride with family and friends, ride with strangers). Thus, the study aims to measure overall tendencies toward using AV-based ridehailing services, rather than focusing on choices presented in the context of individual (hypothetical) trips. The proposed model system is enhanced by the inclusion of several latent attitudinal constructs to account for their influence in shaping mobility choices and willingness to share rides with strangers. A host of socioeconomic 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 (*22*).

The remainder of the paper 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 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 into the endogenous variables and attitudinal indicators used in the modeling effort are furnished.

Survey Data

The data set used in this study was derived from a comprehensive survey conducted in 2019 in four automobile-oriented metropolitan areas of the United States: Phoenix, AZ, Austin, TX, Atlanta, GA, and Tampa, FL. The survey was specifically aimed at gathering very detailed information about attitudes and perceptions toward emerging transportation technologies such as ridehailing services, micromobility technologies, and AVs. The survey also gathered detailed socioeconomic, demographic, and mobility behavior data so that the responses of individuals to questions about ridehailing services and AVs could be placed in an appropriate context. Full details about the survey instrument, questions/content, sampling strategies, response rates, and weighting methods are documented in the study by Khoeini et al. (*23*).

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 were adults (aged 18 or older) residing in one of the four metropolitan areas of the United States. Table 1 provides an overview of the unweighted sample characteristics. A slightly larger share of females (at 57%), and a somewhat larger share of young individuals aged 18 to 30 (at 26%) were found in the respondent sample. Only 6.6% of respondents reported not having a driver's license. Just over half of the sample was employed with 26.8% of the respondents indicating that they were neither a worker nor a student. Educational attainment distribution showed that the sample was fairly well-educated overall, with 36.5% having a bachelor's degree and 24.5% having a graduate

Table 1. Sample Socioeconomic 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	$25,000–49,999	15.8
Age category		$50,000–99,999	34.1
18–30 years	26.0	$100,000–149,999	21.0
31–40 years	11.4	$150,000–249,999	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 possession		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	Homeownership	
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	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

degree. Just over 70% of the respondents were White and 7.6% were Black. The income distribution showed that 34% fell in the middle household income range of $50,000 to $99,999 per year. The sample showed a good variation across the different income groups. About 40% of the respondents resided in households with three or more members, 70% resided in a stand-alone home, and 68% owned the home in which they resided. The vehicle ownership profile showed that only 4% resided 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 were collected. A smaller percentage of respondents (just 7.6%) were based in Tampa, with the remainder of the sample quite evenly spread across the other three metro areas. It can be seen that the sample depicted a rich variation in the socioeconomic and demographic characteristics, thus rendering it suitable for a multivariate modeling exercise of the type attempted in this research study. As with any survey sample, it was not representative of the wider population and the distributions of several variables did not quite replicate the distributions found in U.S. census data. Therefore, it would not be appropriate to draw behavioral inferences about ridehailing and AV ridesharing usage patterns based on the summary descriptive statistics. Rather, such inferences should be drawn from the results of a multivariate simultaneous equations modeling exercise such as that conducted in this study.

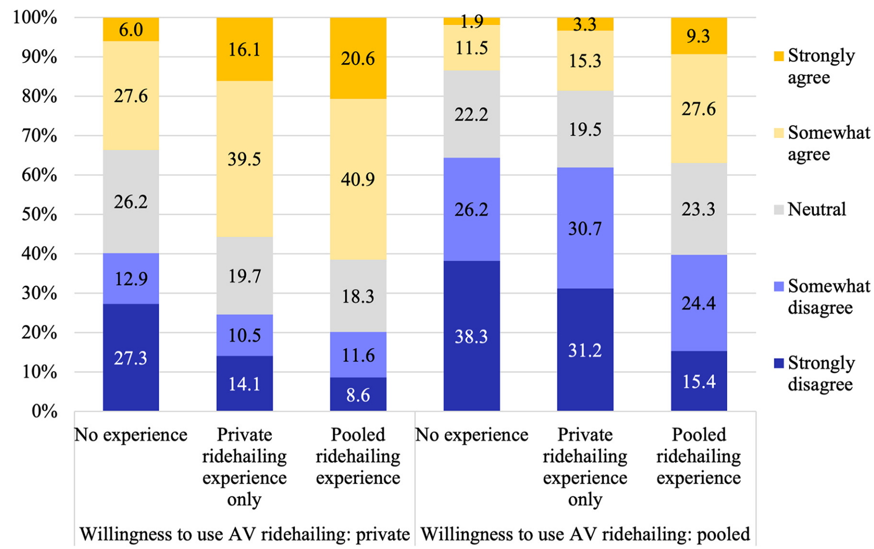

Figure 1. Willingness to use AV ridehailing services by current ridehailing experience ($N = 3,377$).
Note: AV = Autonomous Vehicle.

Endogenous Variables and Attitudinal Indicators

This study aimed to understand user willingness to ride in a future 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 agreed that they would be willing to ride in AV-based ridehailing services (in the future) in each of the modes (bottom of Table 1). As expected, individuals were more agreeable to riding in an AV-based ridehailing service in a private mode, either alone or with friends and family.

It is important to note that when providing answers to these AV-related questions, participants were presented with information about AVs and asked to imagine a future scenario as follows:

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

The primary objective of this study was to examine the potential influence of experiences with using current ridehailing services on the degree to which individuals would be 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 used ridehailing services. Although, at the time of writing, pooled ridehailing services (such as UberPool and LyftShare) were not offered in all four metropolitan areas, they were available in select markets, consequently, some respondents reported having experienced them. Based on their responses to the current ridehailing experience questions, respondents were grouped into three categories:

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

As expected, among individuals who fell into the third group (experienced shared ridehailing services), the vast majority of respondents had 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.

The bivariate chart depicts a discernible pattern, suggesting an association between current experience with using ridehailing services and future intentions to use AV-based services in different modes. The proportion that was not inclined to use AV-based ridehailing services in the future declined as the current experience with ridehailing services was richer. In general, the figure shows that the proportion willing to ride privately in AV-based ridehailing services exceeded that willing to share rides with strangers in an AV-based ridehailing future. This bivariate relationship and the overall socioeconomic profile of the sample rendered 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 comprises attitudes, values, perceptions, and preferences. These traits are often not captured in survey data sets and are 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 incorporated the influence of attitudinal variables within the overall modeling exercise. The survey included many 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 were specified and utilized in this study. They may be termed as "AV technology trust," "discomfort around strangers," and "transit-oriented lifestyle."

The latent constructs used in this study are not uncommon, as similar psychosocial factors have been used in previous studies to analyze mobility choices in the context of emerging transportation technologies. For instance, Batur et al. included driving enjoyment, technology savviness, and environmental consciousness in their study to examine the interest in personal ownership of AVs and their use for running errands (*13*). Similarly, Lavieri and Bhat considered the effects of privacy sensitivity, tech-savviness, variety-seeking lifestyle propensity, and green lifestyle propensity latent constructs when analyzing ridehailing adoption and use frequency, residential location choices, and vehicle ownership (*24*). In research more relevant to the current study, Lavieri and Bhat examined current ridehailing choices and future intentions to use shared rides, and estimated individuals' willingness to share, as well as their values of travel time for different trip purposes (*16*). As that study focused on modeling choices between solo and pooled AV-based ridehailing options for hypothetical trips, their chosen latent constructs (i.e., privacy sensitivity, time sensitivity, and interest in the productive use of travel time) were reflective of those more relevant to shaping mode choices in trip-specific contexts.

Given this background, the current study posited that the three latent constructs chosen for this research would be important determinants of current ridehailing behaviors and the general willingness to use AV-based ridehailing services in the future. The AV technology trust latent construct was intended to capture the respondents' level of trust and faith in the sophistication, reliability, and capabilities of the technology. As familiarity and experience with AVs are likely to affect willingness to share rides in an AV mobility future, it was necessary to capture this effect in this study. As the level of trust in AV technology is likely to be related to familiarity and prior experience (if any) with AVs, it is reasonable to believe that this latent construct would capture, at least to some extent, the influence of any prior experience that respondents may have had with AVs. The discomfort around strangers latent construct aimed to measure the extent to which respondents were concerned about their safety and security when sharing a ride or public space with strangers, as well as their desire for privacy or personal space. This discomfort may lead to a preference for traveling alone or with familiar people, which could ultimately result in a reduced willingness to use both AV-based and traditional ridehailing services in a pooled mode. Finally, the transit-oriented lifestyle latent construct reflected a multimodal lifestyle choice that many people adopt for various reasons, such as environmental concerns, shared mobility preferences, cost savings, and convenience. This lifestyle proclivity is important for understanding ridehailing usage, as people who regularly use public transit may be more likely to use ridehailing services as a complementary mode of transportation to travel to destinations that are not easily accessible by transit. By including this latent construct in the modeling framework, the aim was to disentangle the influence of this lifestyle preference on both current ridehailing usage and the willingness to use AV-based ridehailing services in the future in different modalities.

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 were intuitive and consistent with expectations. For the sake of brevity and given that the distributions and latent constructs are largely self-explanatory, a further in-depth description of the latent constructs is suppressed.

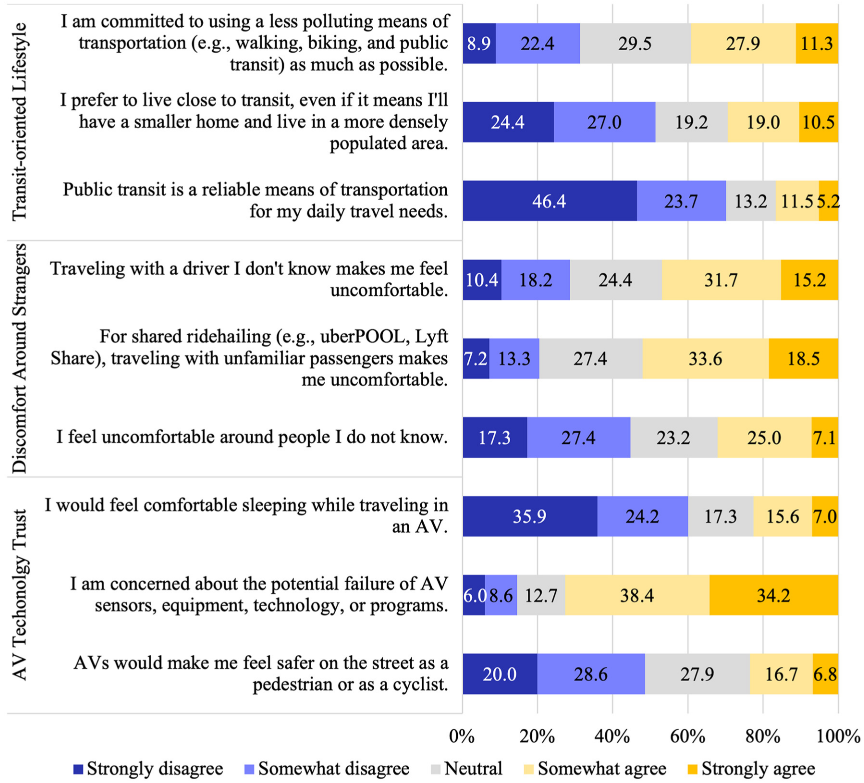

Figure 2. Distribution of attitudinal indicators of latent constructs ($N = 3{,}377$).
Note: AV = Autonomous Vehicle.

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 paper. A detailed exposition of the model formulation and estimation methodology is provided in the Appendix 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 the study by Bhat for details (*22*).

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 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 was 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 supported this hypothesis. A host of socioeconomic, demographic, household, and other travel and built environment attributes were treated as exogenous variables. They were assumed to influence both the latent constructs as well as the main outcomes (endogenous variables). The three latent constructs served as mediating variables; they were both influenced by the exogenous variables, and in turn, they influenced the main outcome variables of interest. Correlations between the attitudinal constructs were accommodated to reflect the possible presence of correlated unobserved factors simultaneously affecting multiple behavioral measures and latent attitudinal variables. This was possible because the latent attitudinal constructs were treated as stochastic variables with a random error term. Because error correlations between the latent constructs were explicitly accommodated in the model formulation, it was not necessary to separately specify error correlations between the main outcome variables. The error correlations between the latent constructs engendered error correlations between the main outcome variables by virtue of the joint model specification

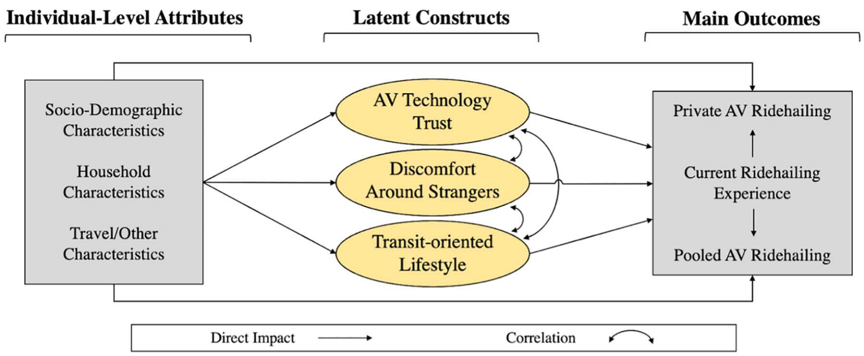

Figure 3. Model structure and behavioral framework.

in which all parameters and relationships were estimated simultaneously in a single step using the GHDM methodology (*22*). Thus, the model structure accounted 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 (*22*).

Modeling Methodology

The modeling methodology adopted in this study was a special case of the GHDM developed by Bhat (*22*). The model was adapted to accommodate one multinomial (nominal) choice variable (corresponding to current ridehailing experience) and two ordinal choice variables (corresponding to the 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 constituted two ordinal dependent variables that were 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 served as latent factors that provided a structure to the dependence among the endogenous variables of interest, whereas the latent constructs themselves were explained by exogenous variables and may be correlated with one another in a structural relationship.

There were two components that the GHDM related to the latent factors. The first was the latent variable structural equation model (SEM) and the second was the measurement equation model (MEM) mapping latent factors to their attitudinal measures. The SEM component defined 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 captured the influence of latent factors and socioeconomic variables on the dependent variables of interest. No separate error correlations were estimated because the error terms of the SEM equations (which defined the latent variables) permeated 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 were 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 were estimated at the person level (as a stochastic function of individual socioeconomic attributes). These latent constructs influenced 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 captured not only unobserved factors affecting the indicator and endogenous outcomes of interest, but also accounted for covariations among the three endogenous variables of the same individual. Thus, the stochastic latent factors helped 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 (*22*, *25*).

Model Estimation Results

Detailed model estimation results are furnished in this section. As the GHDM comprised two components, they are presented and discussed in sequence. It should be noted that model estimation was performed on the unweighted sample data sets. In a multivariate modeling context, it is not necessary to use weighted sample data sets for model estimation to obtain parameter estimates with desirable statistical properties. As shown earlier in Table 1, the sample depicted a rich variation in socioeconomic and demographic characteristics, thus rendering the data sets suitable for model estimation and behavioral inference purposes.

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 were influenced by a host of socioeconomic and demographic variables.

As expected, younger individuals exhibited a higher level of trust in technology and embraced a transit-oriented lifestyle more than older age groups; these findings were consistent with expectations and prior literature (*26*, *27*). Older individuals were less comfortable around strangers, reflecting a more cautious attitude that comes with age. Females reported trusting technology less and being more uncomfortable around strangers owing to privacy and security concerns (also reported by Sener et al. [*21*]). Blacks depicted a lower trust in AV technology, presumably owing 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 (*28*). Students were more likely to embrace a transit-oriented lifestyle (consistent with expectations and findings reported by Brown et al. [*29*]), whereas individuals who were both workers and students trusted AV technology more so than others. This is likely to be a reflection of the greater exposure to technology experienced by individuals who are both workers and students. Households that constitute a nuclear family were less likely to be transit-oriented; households with children probably reside in lower density suburban neighborhoods and are therefore more car-oriented than other types of households that may reside in urban contexts (*30*). Lower income individuals were more transit-oriented whereas high-income individuals depicted a higher level of trust in AV technology. The error correlations showed 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., being more adventurous and risk-taking) are likely to contribute to lower levels of discomfort when around strangers. On the other hand, there was a positive error correlation between AV technology trust and transit-oriented lifestyle, whereas there was a negative correlation between discomfort around strangers and transit-oriented lifestyle. Those who valued privacy (uncomfortable around strangers) were likely to eschew a transit-oriented lifestyle in favor of an automobile-oriented lifestyle. These findings were consistent with expectations, justifying the adoption of a joint simultaneous equations model.

The lower half of the table shows the equivalents of the factor loadings of latent variables on the attitudinal indicators. AV technology trust was positively associated with feeling safe on the streets with AVs present and feeling comfortable sleeping in an AV, but negatively associated with concerns about potential technology failure. These were behaviorally intuitive and statistically significant loadings. For discomfort around strangers, all three loadings were positive; the attitudinal statements corresponded to indicators that measured the degree of discomfort around unknown people, discomfort traveling with unfamiliar passengers, and discomfort traveling with a driver who is not known, and therefore the positive loadings were behaviorally intuitive. Finally, the transit-oriented lifestyle construct was associated positively with attitudinal indicators measuring the extent to which individuals felt 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 had behaviorally intuitive signs and were statistically significant. These three latent constructs were used in the MEM 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 endogenous choice model component. This component corresponds to the behavioral outcomes of interest, namely ridehailing experience and willingness to use future AV-based ridehailing services in a private (alone or with friends/family) and shared/pooled (with strangers) mode.

The key findings of interest relate to the endogenous variable and latent construct effects. It can be seen that current ridehailing experience had 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) were, as expected, more likely to be willing to engage in private AV-based ridehailing services in the future. However, they were not more likely to engage in shared AV-based ridehailing

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

Explanatory variables (base category)	Latent construct model					
	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
I 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: AV = Autonomous Vehicle; 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.

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

Explanatory variables (base category)	Main outcome variables							
	Current ridehailing experience (base: no experience)							
	Private only experience		Pooled experience		Private AV ridehailing (ordered, 5-level)		Pooled AV ridehailing (ordered, 5-level)	
	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 (*)								
\$50,000–99,999	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
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 and 40 mi	na	na	na	na	na	na	–	–
Population density (high population density area)								
Low population density area (< 2,900 persons/mi^2)	−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

(continued)

Table 3. (continued)

Explanatory variables (base category)	Main outcome variables							
	Current ridehailing experience (base: no experience)							
	Private only experience		Pooled experience		Private AV ridehailing (ordered, 5-level)		Pooled AV ridehailing (ordered, 5-level)	
	Coef	*t*-Stat	Coef	*t*-Stat	Coef	*t*-Stat	Coef	*t*-Stat
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	−12,090.58				−3710.01			
Log-likelihood at constants	−13,842.57							
Number of parameters	116				79			
Likelihood ratio test	0.127				0.103			
Avg. prob. of correct prediction	0.039				0.035			

Note: AV = Autonomous Vehicle; Avg. = average; Coef = coefficient; – = not statistically significantly different from zero at the 90% level of confidence; na = not applicable; GHDM = generalized heterogenous data model.
*Base category is all other complementary categories for the correspondent variable.

services. On the other hand, individuals who had experienced pooled ridehailing services (currently) were more likely to be willing to ride future AV-based ridehailing services in both a private and a shared mode. In other words, people need to have experienced 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 will need to be deployed to enhance a shared mobility future.

Latent attitudinal factors also played a key role in shaping the endogenous outcomes of interest. As expected, AV technology trust positively influenced the willingness to ride AVs in a private or shared mode. Those who were uncomfortable around strangers were less likely to use current ridehailing services (either in a private or pooled mode), which was 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 influenced the likelihood of being willing to ride future AV-based services in a shared mode. A transit-oriented lifestyle proclivity was, however, associated with a greater likelihood of being willing to ride future AV-based ridehailing services in a shared mode, presumably because such individuals were more open to using shared modes of transportation in which fellow passengers are strangers. This is another set of key findings that has important implications for the types of awareness campaigns and messaging that may be needed to overcome attitudinal barriers to adoption of a shared mobility future. The rest of Table 3 shows exogenous variable effects, and a detailed exposition is not offered here in the interest of brevity. In general, it was found that young individuals were more likely to embrace ridehailing, whereas older adults were less likely to do so, similar to those reported in the literature. Interestingly, age had no significant direct effect on willingness to ride AV-services in a shared/pooled mode; however, the indirect effects were mediated through the latent constructs. Although females trusted technology less and were more uncomfortable around strangers (Table 2), they were 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 (*31*), it is likely that they take advantage of the flexibility and convenience of ridehailing services, despite the issues related to technology trust and discomfort with strangers (*28*). Racial differences were 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 both positively influenced ridesharing mode usage but had no direct effect on willingness to ride future AVs in a shared mode. Single adults were more likely to use pooled ridehailing services currently, whereas individuals in two-person households were 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 were more likely to embrace pooled AV ridehailing services, whereas those in the higher income group were more likely to be current users of ridehailing services. Individuals in the middle income age group were likely to be comfortable using technology and had a desire to enjoy the cost savings that come with sharing rides in an AV future. Those who engaged in more online shopping (essentially more likely to use technology for fulfilling activities) were more likely to embrace technology in the future; they were 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 half of the coefficient for the private option). Residents of Austin exhibited a greater proclivity toward 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 expressed a greater likelihood of being willing to try future AV-based ridehailing services in both a private and shared mode. This is probably owing to the familiarity with AV technologies that Phoenix residents enjoy, stemming from the current availability of AV-based ridehailing services in the metropolitan area (people are able to see and experience AVs firsthand). Residents of low population density areas were less likely to use ridehailing services, presumably because such residents have access to their own private automobiles (*32*).

Study Implications and Conclusions

The utopian vision of a sustainable mobility future is often described as one in which ACES vehicles serve the mobility needs of the public. Although 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 AV-based future, this study presented a behavioral choice model of the willingness to ride in future AV-based ridehailing services in a private or shared mode. The private mode entailed riding in such vehicles alone or with friends and family, whereas the shared mode entailed riding with strangers. The model estimation utilized a comprehensive survey data set that included detailed information about attitudes and perceptions toward AVs and ridehailing services, and willingness to ride future AV-based services in private and shared modes. The model was a comprehensive econometric model system that accounted for the influence of current ridehailing experience on the willingness to ride AVs in the future in different modes, which was also treated as an endogenous variable in the model formulation. The model structure incorporated a battery of attitudinal statements represented by three latent attitudinal constructs (capturing lifestyle and mobility preferences) along with the usual host of exogenous socioeconomic and demographic variables that typically influence mobility choices. The data set comprised more than 3,000 adults drawn from the Phoenix, Atlanta, Austin, and Tampa metro areas of the United States.

The model estimation results revealed the following key findings of this study. Firstly, current ridehailing experiences (whether an individual has experienced private or pooled ridehailing services that currently exist in the market) significantly influenced the likelihood of being willing to ride in AV-based services in the future. Secondly, mere private ridehailing experiences, however, were not sufficient to bring about a higher proclivity toward embracing shared AV-based ridehailing services in the future. Lastly, experience riding current ridehailing services in a pooled mode did significantly enhance the likelihood of being willing to ride future AV-based services in a shared mode.

The reality is that experience matters; it outweighs any amount of literature, brochures, publicity campaigns, and media coverage when it comes to overcoming the barriers and hesitation to share rides with strangers. Whether it be the discomfort of being close to strangers, the inconvenience of increased wait and travel times resulting from trip circuity, or a desire for privacy, there are numerous barriers to the widespread adoption of AV-based ridehailing services in 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 (*33*). This also speaks to the need to reimagine future AV designs, in which 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 Phoenix indicated a higher proclivity toward embracing an AV-based mobility future in both private and shared modes. This finding is very likely because of 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, advances a greater degree of willingness to embrace it. The study results showed that attitudes, perceptions, and preferences strongly influenced the willingness to ride AVs in different modalities. Trust in technology was critical as it positively affected the proclivity to ride AVs in both modes. However, discomfort with strangers remains a barrier. Educational awareness campaigns should be aimed at making the 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 the 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.

One limitation of this study is that the willingness to use AV-based mobility services in a shared/pooled mode may very well depend on trip-level characteristics, which are not included in the model specification developed. The trip purpose, the urgency and time sensitivity of the trip, the cost savings associated with pooling, and the nature and size of the vehicle may play a critical role in shaping willingness to share rides with strangers. Thus, there is a place for both types of studies—studies that view willingness to share in a broader contextual basis (such as this study) and studies that examine the use of shared modes in specific trip contexts (such as Lavieri and Bhat [*16*]).

Another limitation of this study is that it uses survey data collected before the COVID-19 pandemic, and therefore the results may not necessarily reflect individuals' current attitudes and behaviors toward shared modes. Following the pandemic, attitudes reflecting a transit-oriented lifestyle and discomfort around strangers are likely to have altered significantly. Future research is needed to explore the stability of attitudes and behaviors in a post-pandemic world, particularly in the context of emerging transportation technologies and their potential implications on the transportation system (*34–38*). On a related subject, one might question the relevance of the latent constructs considered in this study, given that only three latent variables were investigated from a wide range of alternatives. Future research should investigate the influence of additional latent factors on ridehailing experiences, such as positive ridehailing experience, positive transit experience, transit dependency, technology savviness, and environmental proclivity. Furthermore, for private ridehailing trips, this study made no distinction between solo rides and shared rides with family and friends. Because riding with friends/family allows people to spend time together, future research should work to draw a distinction between different types of private ridehailing trips. Addressing this limitation may allow for a more nuanced understanding of the behavioral phenomena in this study.

Author Contributions

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

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Supplemental Material

Supplemental material for this article is available online.

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