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Modeling Individuals' Willingness to Share Trips with Strangers in an Autonomous Vehicle Future

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Project Title: *Capturing the Impacts of Ride-sourcing and HOVs*

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16. Abstract

The potential of dynamic ridesharing as a Mobility-as-a-Service centerpiece in cities that are not dense enough for viable and effective public transit systems is being extensively studied by transportation supply researchers. With the era of autonomous vehicles quickly approaching, dynamic ridesharing services could have an important role in increasing vehicle occupancy, reducing vehicle miles traveled, and improving traffic conditions. However, the extent to which these potentials can be achieved depends on consumers' disposition to sharing rides. From a travel behavior perspective, two essential elements to the adoption of shared rides are individuals' acceptance of increased travel times associated with pick-up/drop-off of other passengers and their approval of strangers sharing the same vehicle. The current study develops the notion of willingness to share (WTS), which represents the money value attributed by an individual to traveling alone compared to riding with strangers, to investigate the adoption of shared rides. Using a multivariate integrated choice and latent variable approach, we examine current choices and future intentions regarding the use of shared rides and estimate individuals' WTS as well as their values of travel time for two distinct trip purposes. Results show that users are less sensitive to the presence of strangers when in a commute trip compared to a leisure-activity trip. We also observe that the travel time added to the trip to serve other passengers may be a greater barrier to the use of shared services compared to the presence of a stranger. However, the potential to use travel time productively may help overcome this barrier especially for high-income individuals.

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1. Introduction

After a decade of worldwide development and popularization of new transportation services, private automobile ownership is no longer the obvious synonym for flexible and convenient travel. To capitalize on the potential substitution of drive alone trips by alternative service-based travel, Mobility-as-a-Service (MaaS) Systems propose the use of information and communication technologies (ICTs) to create online platforms that provide users with multiple options of personalized door-to-door trip plans based on an interconnected network of public and private transportation services (such as public transit, bicycle-sharing, car-sharing, and ride-hailing[1]) and an integrated payment system (Jittrapirom et al., 2017).

Most of the currently existing MaaS schemes are established in Europe and have public transit as a main structuring component, while other modes, such as bicycle and car-sharing, are used as first and last mile connectors (see Jittrapirom et al., 2017 and Nikitas et al., 2017). However, for MaaS systems to become prevalent across the U.S, an alternative structuring travel mode may become necessary. Many U.S. metropolitan areas have medium and low-density land use patterns (extended across large areas) and less-than-adequate public transit systems with restricted coverage, which limits the interconnectivity between travel modes and door-to-door travel. A possible solution to this problem is the expansion of micro-transit or dynamic ridesharing services (Frei et al., 2017). Micro-transit refers to private multi-passenger transportation services (using SUVs, mini-vans or shuttle buses), that serve passengers using dynamically generated routes that may require passengers to make their way to and from common pick-up or drop-off points (USDOT-FTA, 2018). Dynamic ridesharing (also known as real-time ridesharing, ride-splitting, or pooled ride-hailing) is similar to micro-transit in the sense that multiple users share the same ride and routes are dynamically determined, but the latter service relies on drivers' non-commercial vehicles (allowing fewer passengers per ride) and has pick-up and drop-off locations defined by the users (current examples of these services are UberPOOL and Lyft Line)[2,3]. In summary, both services aim to provide flexible travel, while increasing vehicle occupancy rates by matching users with similar routes to the same vehicle, and consequently decreasing the number of vehicles circulating, and reducing traffic congestion and the associated environmental footprint.

From a supply perspective, dynamic ridesharing and micro-transit are receiving significant attention from researchers (for some recent studies, see Frei et al., 2017, Levin et al., 2017, and Wang et al., 2018). These and related simulation-based studies have

[1] Ride-hailing services, also referred to as transportation network companies (TNCs), use a smartphone or web application to pair passengers with drivers who offer paid rides in their non-commercial vehicles. The service is analogous to a taxi, but offers scheduling and pricing advantages. The largest and most well-known ride-hailing company in the U.S is Uber.

[2] Uber has recently released a new service that is called "Express Pool" in which users are required to walk to specific pick-up and drop-off locations in exchange of an even cheaper fare than the regular Uber Pool, which tightens even more the definition of both services.

[3] Note that some studies (especially before the dissemination of ride-hailing) use the term dynamic ridesharing as a synonym for ICT-enabled dynamic carpooling. In this case, an individual going to a specific place can use an online application to offer a ride (paid or not) to another individual going to a similar destination. In our study, we use the "newer" meaning of dynamic ridesharing, in which users split a hailed ride.

explored future scenarios where autonomous vehicles (AVs) are available and ride services are provided by TNCs operating shared autonomous vehicles (SAVs) fleets. The studies suggest that dynamic ridesharing through SAVs has good potential to quite substantially reduce overall VMT relative to the case of privately owned AVs, and also that additional travel times due to pick-up and drop-off of multiple passengers could be compensated by reductions in congestion if shared rides are massively adopted by users.

Although simulation-based studies are optimistic about the potential for dynamic ridesharing systems, the performance of these services in terms of matching users, reducing pick-up waiting times, and increasing vehicle occupancy is directly dependent on public acceptance and consequent penetration rates. Unfortunately, historical data shows that sharing rides (in all different forms) has not been popular among U.S. travelers (Chan and Shaheen, 2012). Scheduling constraints have admittedly been an important barrier to the acceptance of traditional carpooling, since trips had to be identified a priori and both drivers and passengers had relatively little flexibility to make last minute changes in travel plans (Chan and Shaheen, 2012). While this reduced flexibility of carpooling has been solved by real-time scheduling and ride-hailing features, users still need to accept the potentially longer travel times of a shared ride due to pick-up/drop-off of additional passengers. In addition, another apparent obstacle to the expansion of dynamic ridesharing is the users' willingness-to-share rides with strangers. Recent studies indicate that travelers are hesitant about being in an automobile environment with unfamiliar faces due to distrust, security and privacy concerns (see, for example, Morales Sarriera et al., 2017 and Amirkiaee and Evengelopoulos, 2018).

In this context, future planning towards SAVs and MaaS systems in U.S. cities and studies examining the potential impacts of dynamic ridesharing on transportation networks could benefit from a deeper understanding of behavioral aspects associated with the acceptance of shared rides by travelers. Specifically, understanding psychosocial and financial trade-offs associated with preferences toward fare discounts, travel times, and presence of strangers in the vehicle can help identify segments of the population that are more (and less) prone to adopting dynamic ridesharing. To address this need, the current study develops the notion of willingness to share (WTS), which represents the money value (willingness to pay or WTP) attributed by an individual to traveling alone (i.e., to not share) compared to riding with strangers. Individuals' WTS is examined together with their values of travel time (VTT), enabling a comparison between people's sensitivities to delays (associated with serving multiple passengers) and their concerns about being in a car with strangers.

To investigate WTS and VTT, we develop a joint model of current ride-hailing experience and future intentions regarding the use of driver-less SAV services for commute and leisure trip purposes. Current ride-hailing experience is represented as a nominal dependent variable with three categories: (1) no experience with ride-hailing services, (2) experience only with private services (the individual traveled alone or with people s/he knew), and (3) experience with private and pooled services (the individual has, at least once, traveled with strangers for a cheaper fare). The future intention outcomes are represented as two binary outcomes corresponding to the choices between: (1) shared-ride and solo-ride in a SAV for a commute trip, and (2) shared-ride and solo-ride in a SAV for a leisure trip (both stated choice outcomes have three repeated choice occasions). The three outcomes (current ride-hailing experience and the two future SAV use choices) are jointly modeled as functions of unobserved psycho-social stochastic latent constructs, and observed transportation-related choices and sociodemographic variables. The current level of ride-hailing experience is assumed to affect the future choices of riding solo or sharing rides, which enables the evaluation of how current exposure to shared (or solo) rides may affect individuals' future intentions. The joint approach allows for the underpinning of the true effect of the current experience since we are able to control for common unobserved factors underlying all choice dimensions through the stochastic latent constructs. The modeling methodology is a special case of Bhat's (2015a) Generalized Heterogeneous Data Model, where the outcomes include one nominal outcome and two binary outcomes. However, unlike earlier implementations of the GHDM, we have a combination of one cross-sectionally observed variable (this is the nominal variable corresponding to current ride-hailing experience) and two variables with repeated choice observations (these correspond to the future intention outcomes).

Three stochastic psychological latent constructs representing *privacy-sensitivity*, *time-sensitivity*, and *interest in productive use of travel time (IPTT)* are modeled as functions of socio-demographic characteristics and used to create dependency among the nominal outcome and binary outcomes, and across the multiple choice-occasions. Additionally, the stochastic latent constructs are interacted with two attributes of the stated choice alternatives (time and number of additional passengers) to accommodate individual heterogeneity in VTT and WTS.

The data used is drawn from an online survey, developed and administered by the authors in the fall of 2017, of 1,607 commuters in the Dallas-Fort Worth-Arlington Metropolitan Area (DFW) of Texas, U.S. DFW is the largest metropolitan area in Texas in terms of population and the fourth largest in the U.S. It has more than 7.4 million inhabitants and is the fastest growing metropolitan area in the country (U.S. Census Bureau, 2018a). DFW is a car-dominated urban area where more than 81% of commute trips are undertaken using the drive alone mode and another 10% are pursued by a private car even if not alone. The current drive alone-dominated modal split and limited transit infrastructure in the DFW area makes it suitable as a potentially good location for the use dynamic ridesharing as a core component to facilitate the development of a MaaS system.

The remainder of this paper is organized as follows. The next section provides a detailed description of the survey, stated choice experiment, and sample used in the study. Next, in Section 3, we introduce the conceptual and analytic framework, including the procedure to compute VTT and WTS. Section 4 presents the results of the model, while Section 5 discusses policy implications. Conclusions and future research recommendations are provided in the final section.

2. Data

The data used for the analysis was obtained through a web-based survey. The distribution was achieved through mailing lists held by multiple entities (local transportation planning organizations, universities, private transportation sector companies, non-profit organizations, and online social media). To focus on individuals with commute travel, the survey was confined to individuals who had their primary work place outside their homes. The final sample used in the current paper includes information on 1,607 respondents.

To obtain information on the respondents' experience with ride-hailing services, the survey first provided definitions of both ride-hailing ("Ride-hailing services use websites and mobile apps to pair passengers with drivers who provide passengers with transportation in the driver's non-commercial vehicle; Examples are Uber and Lyft."), and pooled ride-hailing services ("In the carpooling option of ride-hailing, additional passengers with similar routes get picked and dropped off in the middle of the customer's ride; Customers receive discounted rates when they choose this option"). Then, before the stated choice experiments, respondents were presented with the definition of autonomous vehicles, as "Self-driving vehicles, also known as *autonomous cars* or *driverless cars*, are capable of responding to the environment and navigating without a human driver controlling the vehicle. In the following questions, whenever you read the term *self-driving vehicle*, imagine a car with no steering wheel that operates like a personal chauffeur". Respondents also were provided the option to watch a 90-second educational animation video about how AV-technology works and how the user experience might be.

Considering the uncertainties associated with the AV future, the stated choice experiment design focused on simple scenarios that would allow the simultaneous investigation of VTT and WTS without imposing too many assumptions about changes in urban mobility. Respondents were presented with situations with only binary alternatives, and both alternatives involving the use of an SAV (corresponding to traveling in an SAV alone or with strangers). Five trip attributes characterized each scenario, and were varied across scenarios: (1) travel time (which was associated with a specific distance for fare calculation purposes), (2) fare structure, (3) reduced cost amount for sharing, (4) additional travel time associated with sharing, and (5) the number of additional passengers. All the attributes and their respective levels are presented at the top of Figure 1.The levels for the travel time attributes (the first and the fourth attributes above) were defined with the objective of keeping the scenarios realistic, while also providing an instrument to engender adequate time variability in the attribute values across scenarios. For the second attribute, fare structure, a three-level scheme was used. The first level assumed that there would be no change in the non-pooled fare structure compared to today (this fare structure was based on Uber's non-pooled distance-based and time-based fare structure at the survey time; see UberEstimator, 2017). The other two levels (reflecting an autonomous vehicle future) assumed that service fees would no longer be necessary (because of the absence of human drivers) and that there would be a certain percentage reduction in the distance-based fare (relative to the current Uber fare structure). For the third attribute, corresponding to the reduced cost due to sharing, no specific source of information about current TNC procedures was readily available, but the anecdotal experience of several students at the University of Texas suggested significant variability. Hence, three levels corresponding to 20%, 40%, and 60% reduction (relative to the solo-SAV rate) were used in the stated choice experiments. The number of additional passengers was defined considering that standard autonomous cars would accommodate comfortably up to four passengers (similar to today's passenger vehicles, leading to three levels for this attribute, corresponding to one, two, and three additional passengers). In all, there were 243 (5 attributes corresponding to the five columns in Figure 1 and 3 levels corresponding to the three rows of Figure 1, for a total of $3^5 = 243$) possible combinations between the attribute levels. From these combinations, 27 different scenarios were chosen with the focus on isolating main effects and keeping orthogonality. As illustrated at the bottom of Figure 1, the respondent was presented with two alternatives and the information available for each alternative was the total travel time, cost, and, in the case of shared rides, the additional number of passengers. In other words, the discount rates and additional travel times due to pooling were not explicitly shown, but incorporated in the travel time and cost of the shared alternative. Each individual responded to six scenarios evenly split between commute and leisure trip purposes.

Experimental Design Attributes and Levels				
Solo option		***Shared option***		
Fare structure	**Travel time**	**Discount**	**Additional travel time**	**Additional passengers**
Base fare: $1 Cost per minute: $0.1 Cost per mile: $0.91 Service fee: $2.45	10 minutes	20%	4 minutes	1
Base fare: $1 Cost per minute: $0.1 Cost per mile: $0.70 Service fee: $-	15 minutes	40%	8 minutes	2
Base fare: $1 Cost per minute: $0.1 Cost per mile: $0.40 Service fee: $-	20 minutes	60%	10 minutes	3

Scenario Example	
Imagine that ride-sourcing services (similar to Uber and Lyft) use self-driving vehicles for all of their clients. Imagine also that you plan to go out on a leisure activity and you will use one of these ride-sourcing services. In the three scenarios described below, which option would you choose?	
Option 1	***Option 2***
Call a private self-driving cab service (similar to Uber/Lyft)	Call a shared self-driving cab service (similar to UberPool/LyftLine)
Travel time: 15 min Cost: $16.5 No additional passenger	Travel time: 23 min Cost: $10.0 Additional passengers: 1

Figure 1. Stated Choice Experiment Design Components and Scenario Example

The survey also collected socio-demographic and attitudinal data from the respondents. Table 1 presents descriptive statistics of the socio-demographic characteristics of the sample (a discussion of the attitudinal information collected, and the corresponding descriptive statistics, is deferred until Section 3.1). A comparison of our sample with the employed population of DFW (as characterized by the U.S. Census Bureau, 2018b) indicates that the sample has an overrepresentation of men (58.4% in the survey compared to 54.0% from the Census data), individuals between 45 and 64 years of age (53.2% compared to 35.8%), Non-Hispanic Whites (75.0% compared to 51.0%), and individuals with bachelor's or post-graduate degrees (75.6% compared to 33.7%). We also observe that the majority of the sample corresponds to full time-employees (81.6%). Finally, among the socio-demographic characteristics, we are unable to compare the statistics from our survey with the Census data for the household income and household composition variables, because the Census data provides income and household composition data only for all households (while our survey is focused on households with at least one worker with a primary workplace outside home). However, the sample statistics do suggest a skew toward individuals from higher income households and multi-worker households. Overall, there are many possible reasons for the socio-demographic differences between our sample and the Census data. For example, the main topic of the survey was self-driving vehicles, which may be of more interest to highly educated men. In addition, the survey was conducted strictly through an online platform and the largest mailing list used in the distribution was of toll-road users, who are likely to be individuals with higher values of time that then correlates with the specific characteristics of our sample. In any case, while the general descriptive statistics of the dependent variables of interest cannot be generalized to the DFW population, the individual level models developed in this paper still provide important insights on the relationship between travel behavior and socio-demographic/lifestyle characteristics.

In addition to socio-demographics, we also use a set of three long and medium-term transportation-related variables as exogenous variables: residential location (characterized by urban versus non-urban living), vehicle availability (whether the number of motorized vehicles in the household was less than, equal to, or greater than the number of workers), and commute mode choice (traveling to work by driving alone, non-solo car, or non-car modes). While it can be reasoned that these transportation-related variables are influenced by common unobserved factors affecting the main outcomes, we tested this issue in our model specifications by considering these three variables also as endogenous variables. These three transportation-related variables were not significantly impacted by the latent constructs (at any reasonable statistical level) and, therefore, are treated as exogenous. There are many possible reasons for this result, from lack of variability in the actual variable (for example, only 3.5% of the sample does not drive to work) to inadequacy in the ability of latent variables to explain medium and long-term transportation-related choices (the latent variables, and therefore their indicators, used in this study are directed toward capturing trip-related attitudes in the context of an uncertain future transportation landscape, as discussed in more detail in Section 3.1; long and medium-term choices, on the other hand, are usually associated with overall lifestyles, such as a green-lifestyle or a luxury-orientation, as observed by Bhat, 2015b and Lavieri et al., 2017). The descriptive statistics of the three transportation-related variables are provided toward the bottom of Table 1, and reveal a sample with more than three-fourth of the respondents living in non-urban areas, more than 50% owning motorized vehicles equal to the number of workers in the respondent's household, and a predominance of the drive alone mode to commute to work.

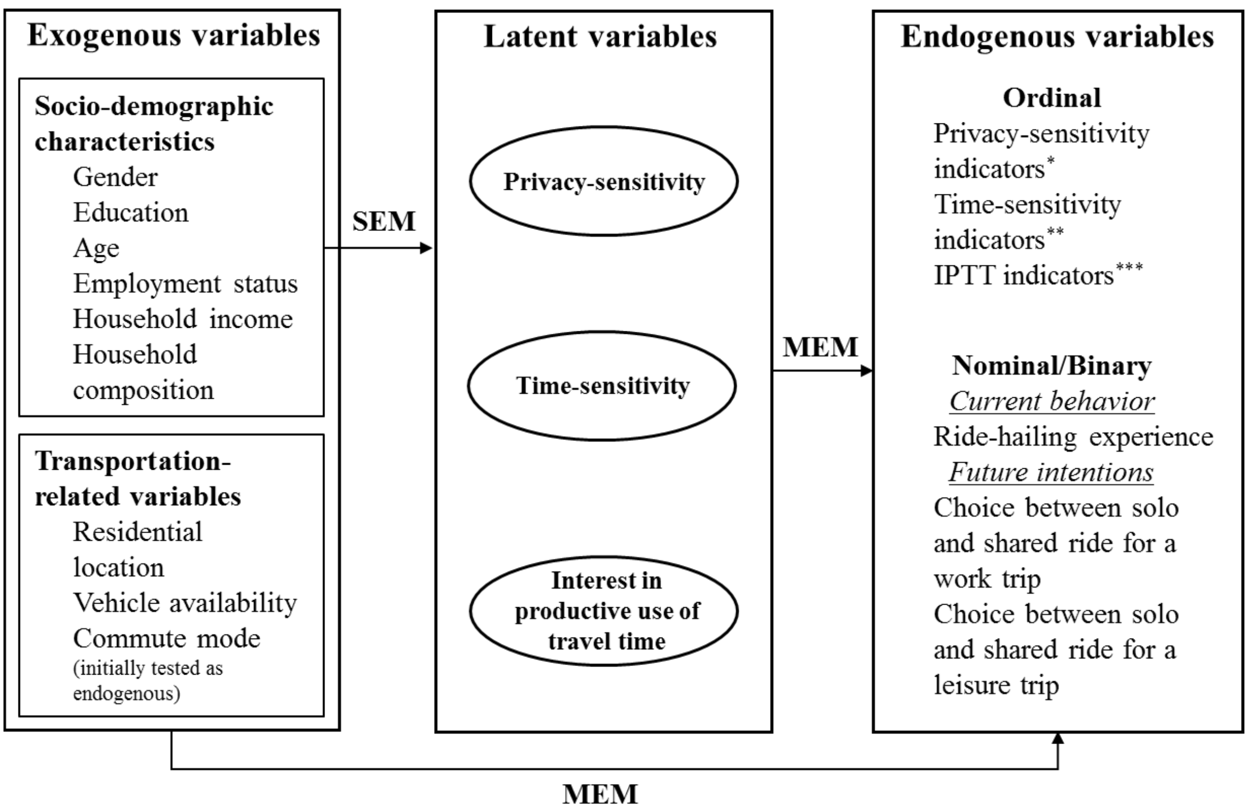
A note on data-related issues before moving to the description of the analytic framework. First, as mentioned earlier, the survey is not representative of the population of employed individuals in DFW and is skewed toward high-income individuals, which may result in inflated VTT and WTS. Second, it is well documented in the literature that stated choice data should be anchored to actual revealed choice values to reduce hypothetical bias and increase the external validity of WTP values (Hensher, 2010). The situation investigated in this study did not have a plausible revealed choice analogous, so WTP is not 'calibrated' by observed choices. Instead, to avoid drawing conclusions directly about actual VTT and WTS values, we direct our analysis toward relative comparisons between these two values for different segments of the population. Finally, while VTT may change from the current case of human-driven vehicles to the situation when individuals are no longer required to drive because of a number of reasons (see Cyganski et al. 2015, Krueger et al., 2016, and Das et al., 2017), we confine our attention in this study on VTT effects associated with being interested in using travel productively, as discussed next.

Table 1. Sample Distribution of Socio-Demographic Characteristics and Transportation Related Exogenous Variables

Variable	Count	%
Gender		
Female	668	41.57
Male	939	58.43
Age		
18 to 34	261	16.24
35 to 44	360	22.4
45 to 54	432	26.88
55 to 64	423	26.32
65 or more	131	8.16
Race		
Non-Hispanic White	1205	74.98
Non-Hispanic Black	102	6.35
Hispanic	109	6.78
Asian/Pacific Islander	101	6.29
Other	90	5.60
Education		
Completed high-school	238	14.82
Completed technical school/associates degree	154	9.58
Completed undergraduate degree	724	45.05
Completed graduate degree	491	30.55
Employment type		
Full-time employee	1312	81.64
Part-time employee	138	8.59
Self-employed	157	9.77
Household income		
Under $49,999	184	11.45
$50,000-$99,999	443	27.57
$100,000-$149,999	496	30.86
$150,000-$199,999	269	16.74
$200,000 or more	215	13.38
Household composition		
Single person household	191	11.89
Single worker multi-person household	265	16.49
Multi-worker household	1151	71.62
Residential location		
Suburban, rural or small town	1232	76.67
Urban (downtown or central area)	375	23.33
Vehicle availability		
< 1 per worker	236	14.69
= 1 per worker	817	50.84
> 1 per worker	554	34.47
Commute mode		
Non-car	56	3.48
Car non-solo	146	9.09
Drive alone	1405	87.43

3. Analytic Framework

Figure 2 provides the conceptual structure for our joint model of ride-hailing experience and stated choice of SAV service for work and leisure trip purposes. Exogenous socio-demographic and transportation-related characteristics (left-side box in Figure 2), and three endogenous stochastic latent constructs representing psycho-social characteristics of the individual (middle box of Figure 2) are used as determinants of the three endogenous variables of interest (ride-hailing experience, and the choices between solo and shared SAV rides for work and leisure trip purposes). Together with these three endogenous outcomes (shown under the label "Nominal/Binary" in the right box of Figure 2), seven attitudinal indicators (representing indicators of privacy-sensitivity, time-sensitivity, and IPTT) help to characterize the three stochastic latent psycho-social constructs. The latent constructs create the dependency structure among all outcomes. A discussion of these latent constructs follows.



"*"I1: I don't mind sharing a ride with strangers if it reduces my costs.
I2: Having privacy is important to me when I make a trip.
I3: I feel uncomfortable sitting close to strangers.
"**"I4: Even if I can use my travel time productively, I still expect to reach my destination as fast as possible.
I5: With my schedule, minimizing time traveling is very important to me.
"***"I6: Self-driving vehicles are appealing because they will allow me to use my travel time more effectively.
I7: I would not mind having a longer commute if I could use my commute time productively.

Figure 2. Model Structure

3.1 Psychosocial Latent Constructs

Three psychosocial latent constructs are considered in our framework: privacy-sensitivity, time-sensitivity, and interest in productive use of travel time (IPTT). These are identified based on earlier studies in transportation and behavioral psychology, and focus on capturing underlying unobserved behavioral aspects that may influence individual's valuation of shared ride attributes. The first latent construct, privacy-sensitivity (characterized by the three attitudinal indicators identified under "*" at the bottom of Figure 2 and labeled as I1-I3 in Figure 3), represents individuals' levels of discomfort and privacy concerns when sharing a vehicle with a stranger. Previous studies have identified that the desire for personal space, aversion to social situations, distrust, and concerns about security are the most relevant behavioral barriers to ridesharing and carpooling services/programs that involve matching between strangers (for example, see Tahmasseby et al., 2016, Morales Sarriera et al., 2017, and Amirkiaee and Evangelopoulos, 2018). Such factors have also been found to be relevant in studies on public transit use (Haustein, 2012 and Spears et al., 2013). Hence, the privacy-sensitivity latent construct is a key element in our model and is hypothesized to have negative impacts on individuals' experience with pooled ride-hailing and choice for shared rides in a SAV context. Additionally, we expect its negative effects to increase with the number of additional passengers (this is a case of the latent variable moderating the effect of an exogenous variable).

The second latent construct is time-sensitivity (see under "**" in Figure 2 and the indicators I4 and I5 of this latent construct in Figure 3). The objective of this construct is to capture people's perceptions of time scarcity and desire in reducing travel time. It is often assumed in transportation studies that an individual's goal is to minimize time traveling. However, as discussed by previous authors (see, for example, Ory and Mokhtarian, 2005), the extent to which traveling is perceived as a disutility may vary among individuals and trip purposes, depending on lifestyle and lifecycle factors and associated activity-scheduling constraints. This latent construct is introduced in the model both as a direct effect on the endogenous variables as well as a moderating effect of the influence of travel time, thereby engendering both observed and unobserved individual heterogeneity in the valuation of travel time.

The final latent construct, interest in the productive use of travel time (IPTT), identified under "***" in Figure 2 and labeled by indicators I6 and I7 in Figure 3, originates in the notion that the ability to use travel time productively may reduce perceived disutilities associated with traveling. This negative effect of time productivity on travel time disutility has been confirmed in the context of rail travel (Gripsrud and Hjorthol, 2012, Frei et al., 2015), and is likely to be relevant in the approaching AV future, as individuals may no longer need to drive and pay attention to traffic (Cyganski et al. 2015, Malokin et al., 2017). This latent construct too is introduced in the model both as a direct effect on the endogenous variables as well as a moderator of travel time effects on the endogenous variables.

All the latent construct indicators are measured on a five-point Likert scale and are modeled as ordinal variables. As may be observed from Figure 3, the sample shows a general tendency toward being privacy-sensitive, time-sensitive, and interested in the productive use of travel time.

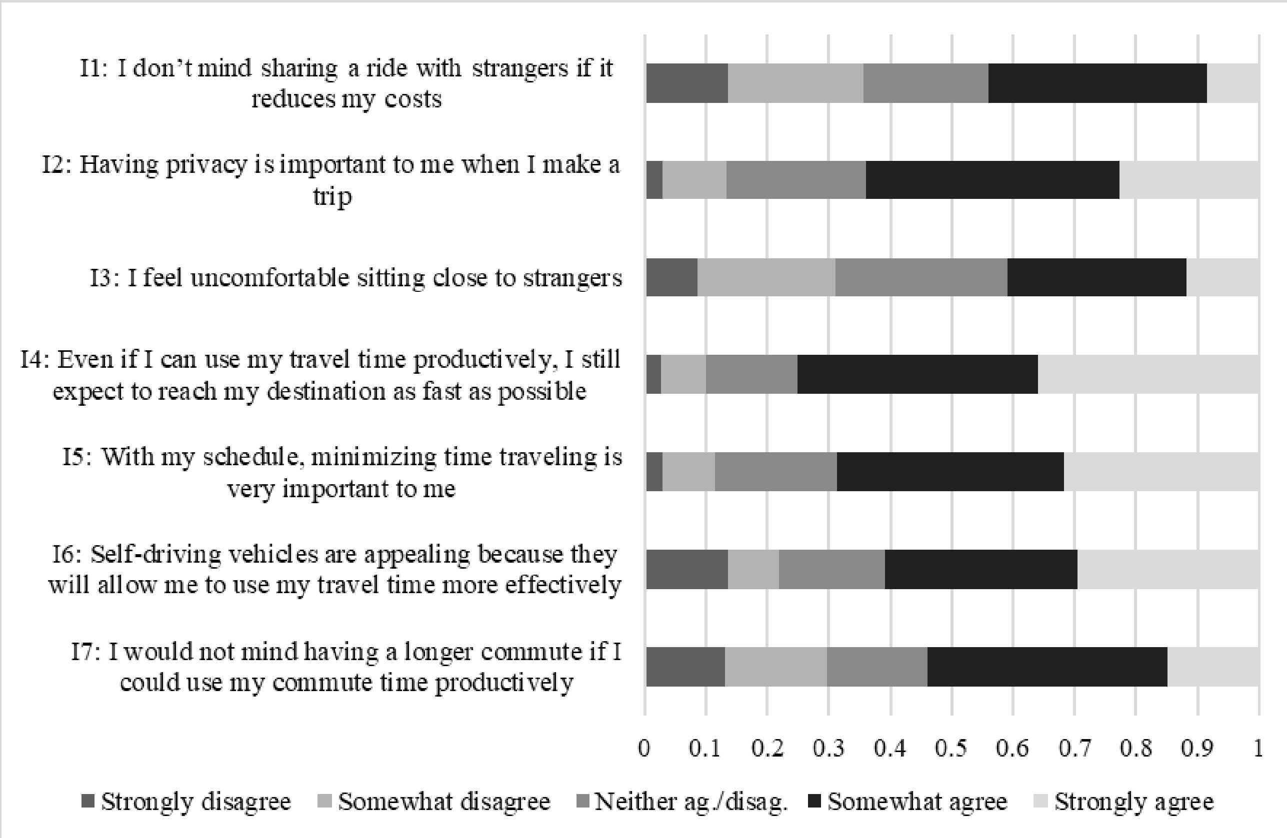


Figure 3. Sample Distribution of Attitudinal and Behavioral Indicators

3.2 Main Outcome Variables

As previously discussed, there are three main discrete choice outcomes in our model associated with individuals' ride-hailing experience (multinomial choice) and the stated choices of SAV service for work and leisure trip purposes (two binary choices). In terms of ride-hailing experience, about 56.4% of the sample (n=906) reported using ride-hailing services at least once in their lifetimes, although only about 10.0% of the sample (n=157) reported experience with the pooled version of the service. Accordingly, ride-hailing experience is represented in the three nominal categories of *no experience* (43.6%; n=701), *experience with private rides only* (46.6%; n=906-157=749), and *experience with pooled rides* (9.8%; n=157; note that this group may have had experience with private rides too). In terms of stated choices for SAV services (n=4821=1607 individuals × 3 choice occasions per individual), we observe that different trip purposes may be associated with different preferences toward sharing. In 48.3% of the choice occasions associated with work trip scenarios, respondents chose to ride alone, while this fraction is higher for leisure trip scenarios, reaching 54.0%. The outcome representing current ride-hailing experience is assumed to impact the stated SAV-service so that we can evaluate how current experiences are shaping future intentions in terms of sharing, while simultaneously controlling for the latent constructs effects on all three choice dimensions.

3.3 Modeling Approach

The model employed in our analysis is a special case of Bhat's (2015a) Generalized Heterogeneous Data Model (GHDM) in which ordinal, nominal, and binary endogenous variables are considered simultaneously. As explained earlier, unobserved psycho-social constructs serve as latent factors that provide a structure to the dependence among the many endogenous variables, while the constructs themselves are explained by exogenous variables and may be correlated with one another in a structural relationship. In this approach, attitudinal indicators are treated as ordinal variables, while the main choice outcomes are nominal or binary. The presence of the stochastic latent variables captures not only the covariances between the attitudinal indicators, but also (a) among the indicators and the observed behaviors of interest as well as (b) between pairs of the observed endogenous variables of interest. Such an approach enables controlling for self-selection effects in the impact of current ride-hailing choice behavior on future intentions in an econometrically consistent fashion. Additionally, the stochastic latent factors serve as a parsimonious approach to incorporating observed and unobserved individual heterogeneity in variables of interest, which is done by interacting the latent factors with exogenous variables. As already indicated, in our application, we interact privacy-sensitivity with the number of additional passengers (strangers) in the shared ride alternatives, and both time-related latent variables with the travel time attribute.

There are two components to the GHDM model: (1) the latent variable structural equation model (SEM), and (2) the latent variable measurement equation model (MEM). As illustrated in Figure 2, the SEM component defines latent variables as functions of exogeneous variables. In the MEM component, the endogeneous variables are described as functions of both latent variables and exogeneous variables. The error terms of the structural equations (which define the latent variables) permeate into the measurement equations (which describe the outcome variables), creating a parsimonious dependence structure among all endogenous variables. These error terms are assumed to be drawn from multivariate normal distributions (with the dimension equivalent to the number of latent variables). The measurement equations have different characteristics depending on the type of dependent variable, 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/binary outcomes of primary interest (see Bhat and Dubey, 2014, and Bhat, 2015a, for details of the formulation and estimation). The latent constructs are created at the individual level (as a stochastic function of individual demographics and transportation-related variables). These stochastic latent constructs influence the current ride-hailing experience endogenous variable in a cross-sectional setting (one revealed observation per individual from each of the 1607 respondents for n=1607) as well as each of the stated choice outcomes (one for commute travel and another for leisure travel) associated with the use of future SAV services in each of the three repeated choice occasions. Doing so immediately and parsimoniously captures not only unobserved factors impacting the indicator and endogenous outcomes of interest (as discussed earlier), but also accommodates covariations among the three choice occasions of the same individual. The resulting GHDM model is estimated using Bhat's (2011) MACML approach. To conserve on space, we do not provide the details of the estimation methodology, which is available in Bhat (2015a).

3.4 Value of Travel Time and Willingness to Share

Within the scope of discrete-choice models, WTP for travel attributes, including time (VTT), corresponds to the ratio of the estimated attribute and cost coefficients. Considering that WTP varies across the population, observed individual heterogeneity is addressed by interaction terms between attributes/cost and socio-demographic characteristics. Unobserved heterogeneity, on the other hand, is usually accommodated by specifying mixing distributions on the attribute coefficients and/or the cost coefficient, or by specifying mixing distributions on the actual WTP ratio coefficient (see Train and Weeks, 2005). A challenge associated with such approaches is that they are profligate in the number of parameters to be estimated. The current study deviates from the traditional WTP and VTT literature by adopting an alternative method to introduce individual heterogeneity in VTT and WTS. Instead of a mixing approach, we use stochastic latent variables as moderators of attributes in the choice utilities, thus capturing both observed and unobserved individual heterogeneity. In addition to a parsimonious structure, this method has the behavioral appeal of partitioning individual heterogeneity in VTT and WTS into specific psycho-social construct effects.

For each individual q, the computations of the expected values of VTT and WTS, and the corresponding variances, occur as follows:

$$E(VTT_q) = \frac{\beta_{TT_1} E(z^*_{TS_q}) + \beta_{TT_2} E(z^*_{IPTT_q}) + \beta_{TT_3}}{\beta_{COST}} \quad , \quad Var(VTT_q) = \frac{1}{\beta^2_{COST}}\left(\beta^2_{TT_1} + \beta^2_{TT_2}\right) \qquad (1)$$

$$E(WTS_q) = \frac{\beta_{AP_1} E(z^*_{PS_q}) + \beta_{AP_2}}{\beta_{COST}}, \qquad Var(WTS_q) = \frac{\beta^2_{AP_1}}{\beta^2_{COST}} \qquad (2)$$

where β_{TT_1} is the coefficient on the interaction of the time-sensitivity latent construct $(z^*_{TS_q})$ and travel time, β_{TT_2} is the coefficient on the interaction of the interest in the productive use of travel time (IPTT) latent construct $(z^*_{IPTT_q})$ and travel time, β_{TT_3} is the coefficient on travel time, β_{AP_1} is the coefficient on the interaction of the privacy-sensitivity $(z^*_{PS_q})$ latent construct and the additional number of passengers (ADD) variable, β_{AP_2} is the coefficient on the ADD variable, and β_{COST} is the coefficient on trip cost. The expected values of the stochastic latent constructs are computed based on the SEM model results.[4]

4. Results

The final model specification was obtained based on a systematic process of testing alternative combinations of explanatory variables and eliminating statistically insignificant ones. Also, for continuous variables such as respondent age and

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[4] The variance formulas arise as given because the latent construct variances are normalized to one for identification in the estimation. Also, to keep the presentation simple, we do not consider the sampling variance of the estimated coefficients in the variance computation.

respondent's household income, a number of functional forms were tested in the sub-models for each endogenous outcome variable, including a linear form, a dummy variable categorization, as well as piecewise spline forms. But the dummy variable specification turned up to provide the best data fit in all cases, and is the one adopted in the final model specification. Also, in the final model specification, some variables that were not statistically significant at a 95% confidence level were retained due to their intuitive interpretations and important empirical implications. In this regard, the methodology used involves the estimation of a large number of parameters, so the statistical insignificance of some coefficients may simply be a result of having only 1,607 respondents. Also, the effects from this analysis, even if not highly statistically significant, can inform specifications in future ride-hailing investigations with larger sample sizes.

In the next section, we discuss the results of the SEM model component of the GHDM, as well as the latent constructs' loadings on the attitudinal indicators (which are one part of the MEM). In subsequent sections, we discuss the MEM relationships corresponding to the effects of socio-demographic and transportation-related characteristics, and the latent constructs, on the three main outcomes of interest.

4.1 Attitudinal Latent Constructs

The structural relationships between socio-demographic variables representing lifecycle stages and the latent constructs are presented in Table 2. Gender shows no significant effect on the individual's level of privacy-sensitivity and interest in the productive use of travel time (IPTT). Yet, women display higher levels of time sensitivity, which is expected considering that working women are more likely to experience time scarcity relative to men, attributable to lingering gender disparities in household-related activities, including childcare and chauffeuring activities (Fan, 2017, Motte-Baumvol et al., 2017). Younger adults display greater levels of privacy-sensitivity and IPTT. The latter effect is probably associated with higher levels of tech-savviness and ICT usage among younger adults, which facilitates the productive use of travel time (Astroza et al., 2017, Malokin et al., 2017). The first effect, on the other hand, seems less obvious and requires further investigation; however, it may also be related to higher levels of technology use, especially smartphones, by younger generations. There is growing evidence that the use of smartphones is creating a "portable-private bubble" phenomenon, which makes individuals more estranged from their surroundings and less interested in potential social interactions in public spaces (Hatuka and Toch, 2014). Along the same lines, higher smartphone usage also seems to be associated with higher social anxiety and lower social capital building (Bian and Leung, 2015, Kuss et al., 2018). We also observe that individuals between 35 and 44 years of age are more time-sensitive than their younger and older peers. This age range is associated with the beginning of the career peak cycle, and also increased responsibilities associated with raising children and looking after family elders (Nael and Hammer, 2017). Non-Hispanic White individuals tend to be more privacy-sensitive relative to other races, a result that aligns with the higher levels of drive-alone travel and vehicle ownership by this ethnic group (Giuliano, 2003, Klein et al., 2018). As expected, individuals who are more highly educated show greater interest in the productive use of travel time. Higher levels of education are associated with higher tech-savviness and ICT usage (Astroza et al., 2017), as well as greater opportunity to work outside the traditional work place (Singh et al., 2013), which can contribute to the ability to work and be productive while traveling. Being a part-time employee or self-employed is associated with lower time sensitivity, presumably because these employment arrangements provide greater time flexibility than full-time employment. Finally, individuals from households with very high incomes (above US$200,000 per year) show greater privacy and time-sensitivity, and are also more interested in using their travel time productively. The higher privacy-sensitivity among the wealthiest segment of individuals can be a direct result of having more access to private property and/or a need to signal exclusivity through separation and differentiation from others (Chevalier and Gutsatz, 2012, Bhat, 2015b). These individuals may also focus on privacy due to concerns associated with safety and preservation of material assets. High-income individuals also have stronger feelings of time pressure (DeVoe and Pfeffer, 2011, Chen et al., 2015), which are dictated by perceived opportunity costs, among other factors, such as increased occupation responsibilities. Such characteristics explain the positive impacts of income in the two time-related latent constructs.

All three correlations corresponding to the three pairs of latent variables are statistically significant (see Table 2), even if only medium-to-low in magnitude. Privacy-sensitivity is positively associated with time-sensitivity, and negatively related to IPTT. Time-sensitivity is also negatively associated with IPTT. The implication of these correlation results is that, when dealing with individuals who are intrinsically privacy and time-sensitive (due to unobserved personality characteristics), an environment that is conducive to the productive use of travel time will have little to no effect on increasing their tolerance to increased travel times and/or additional passengers.

The SEM estimation is made possible through the observations of the endogenous variables (far right block of Figure 3), which include the latent variable indicators and the three endogenous outcomes of interest. The loadings of the latent variables on their indicators are represented at the bottom of Table 2 and have the expected signs. Thresholds and constants associated with the ordinal response equations characterizing the indicators were also estimated but are omitted to conserve on space.

Table 2. Determinants of Latent Variables and Loadings on Indicators

Variables (base category)	Structural Equations Model Component Results					
	Privacy-sensitivity		Time-sensitivity		IPTT	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Gender (male)						
Female	--	--	0.183	4.27	--	--
Age (≥55 years)						
18 to 34	0.168	1.84	--	--	0.326	4.87
35 to 44	0.137	4.09	0.265	5.26	0.256	4.54
45 to 54	--	--	--	--	--	--
Race (other races)						
Non-Hispanic White	0.131	3.76	--	--	--	--
Education (≤ undergraduate degree)						
Graduate degree	--	--	--	--	0.133	4.32
Employment (full-time)						
Part-time employee	--	--	-0.382	-4.71	--	--
Self-employed	--	--	-0.119	-1.97	--	--
Household income (< $150,000)						
$150,000-$199,999	--	--	--	--	0.092	2.84
$200,000 or more	0.350	5.16	0.298	4.26	0.092	2.84
Correlations between latent variables						
Privacy-sensitivity	1.000	n/a				
Time-sensitivity	0.241	7.59	1.000	n/a		
IPTT	-0.115	-2.67	-0.071	-2.71	1.000	n/a
Attitudinal Indicators	**Loadings of Latent Variables on Indicators (MEM component)**					
I don't mind sharing a ride with strangers if it reduces my costs (inverse scale)	0.847	13.98				
Having privacy is important to me when I make a trip	0.477	17.49				
I feel uncomfortable sitting close to strangers	0.347	3.16				
Even if I can use my travel time productively, I still expect to reach my destination as fast as possible			0.755	40.40		
With my schedule, minimizing time traveling is very important to me			1.329	57.60		
Self-driving vehicles are appealing because they will allow me to use my travel time more effectively					1.183	7.26
I would not mind having a longer commute if I could use my commute time productively					0.751	4.49

"--" = not statistically significantly different from zero at the 90% level of confidence and removed from the specification.
"n/a" = not applicable

4.2 Ride-Hailing Experience

The results of the ride-hailing experience model are presented in the first column of Table 3. The coefficients represent the effects of variables on the utilities of private only ride-hailing and shared (or pooled) ride-hailing, with the base alternative being the case of no ride-hailing experience.

The latent variable effects have the expected directionality of effects, with privacy-sensitive individuals less likely to have experience with pooled ride-hailing service and IPTT increasing the probability of both types of ride-hailing experience. This latter result suggests that interest in using travel time more productively is an important factor currently guiding ride-hailing adoption.

In addition to the indirect socio-demographic influences through the latent variable effects just discussed, there are direct socio-demographic effects on ride-hailing experience. Table 3 indicates that age has a direct negative effect on ride-hailing experience, with younger individuals more likely than their older counterparts to have used ride-hailing both in the private as well as pooled arrangements, which is consistent with some earlier studies (Smith, 2016, Kooti et al., 2017). Note that this direct negative age effect more than compensates for the average indirect positive age effects on experience with both private and pooled services through the privacy-sensitivity latent construct. Thus, for example, the average indirect age effect indicates that an individual 18-34 years of age (relative to a person 65 years of age or older) has a lower pooled ride-hailing utility valuation of the order of 0.168 (the coefficient on the "18 to 34 years" of age variable corresponding to privacy sensitivity in Table 2) times the average expected value of the privacy-sensitivity latent variable (0.246) multiplied by -0.131 (the magnitude of the coefficient on the privacy-sensitivity construct on pooled ride-hailing experience in Table 3) yielding an average indirect age effect between the "18 to 34 years" age group and the ">=65 years age group" of -0.005 (=0.168*0.246*(-0.131)). The corresponding direct age effect is 0.843, which swamps the indirect age effect, resulting in younger adults distinctly more likely to adopt the pooled form of ride-hailing compared to their older peers. In terms of the indirect age effects through the IPTT latent construct, these reinforce the negative direct age effects on experience with ride-hailing services (in both private only and pooled arrangements). Again, though, the direct age effect dominates over the indirect age effect through the IPTT latent construct (for example, the indirect age effect through the IPTT construct for the same two age groups as just discussed before is 0.326*0.184*0.151=0.009 for pooled service utility relative to no experience with ride-hailing compared to the corresponding direct effect of 0.843).

The results also show that non-Hispanic Whites are less likely to have used pooled services, even after accounting for the indirect negative effect (through the privacy-sensitivity construct) of being non-Hispanic White (relative to individuals of other race/ethnicity categories) and after controlling for income effects. The reason behind this race/ethnicity effect is not clear in the literature and calls for more qualitative studies investigating cultural influences on the willingness to share rides. However, on a related note, there is evidence that immigrants are more likely to carpool, especially if living in immigrant neighborhoods (Blumenberg and Smart, 2010). Similar to what was observed by Dias et al. (2017), part-time employees are less likely to have experienced private ride-hailing services relative to full-time employees and self-employed individuals.

In terms of household level variables, a higher household income increases experience with both private and pooled ride-hailing, beyond the positive effect of household income through IPTT (and while individuals with a household income over $200,000 have a higher privacy sensitivity, and privacy sensitivity negatively impacts pooled ride-hailing experience, this indirect negative effect gets swamped by the magnitude of the positive direct effect in Table 3; this may be observed by doing a similar computation as for the age effects discussed earlier). Considering that attitudinal and lifestyle factors are being controlled for, the direct positive income effect is probably an indicator of higher consumption power, though there is still a distinct preference for private ride-hailing over pooled ride-hailing in the higher income groups. As we will see later in Section 5.2, the magnitude of the coefficients on the household income variables on the private only and pooled ride-hailing utilities imply that an increase in household income tends to lead to a higher probability of private only ride-hailing experience, at the expense of drawing away from both the pooled ride-hailing and no ride-hailing experience categories. Individuals living alone are more likely to have used private ride-hailing service relative to individuals in other household types, while those in single-worker multi-person households are the least likely to have used both private and pooled services. Individuals living in more urbanized locations are more likely than their counterparts in less urbanized locations to have used both private and pooled ride-hailing. A similar result holds for individuals in households with more than one vehicle per worker. This latter suggests that, in an area such as DFW where almost all households own at least one vehicle, ride-hailing serves as more of a convenience feature for those one-off trips rather than being an accessibility facilitator for routine trips. Still, individuals who commute by non-car modes are more likely to have experience with both private and pooled ride-hailing.

Table 3. Results of the Ride-Hailing Experience and SAV Choice Model Components

Variables (base category)	Ride-hailing experience (base: none)				SAV: work purpose (base: solo)		SAV: leisure purpose (base: solo)	
	Private only		Pooled		Shared		Shared	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Latent variables								
Privacy-sensitivity	--	--	-0.131	-1.90	-1.348	-5.11	-1.251	-7.87
Time-sensitivity	--	--	--	--	--	--	--	--
IPTT	0.151	2.55	0.151	2.55	--	--	--	--
Socio-demographic variables								
Gender (male)								
Female	--	--	--	--	-0.174	-5.23	--	--
Age (≥65 years)								
18 to 34	0.978	9.19	0.843	11.61	-0.311	-1.84	--	--
35 to 44	0.699	7.10	0.564	8.83	-0.257	-3.15	--	--
45 to 54	0.321	4.09	0.336	5.46	--	--	--	--
55 to 64	0.158	2.38	--	--	--	--	--	--
Race (other races)								
Non-Hispanic White	--	--	-0.205	-5.69	--	--	--	--
Education (≤ undergraduate degree)								
Graduate degree	--	--	--	--	--	--	-0.086	-3.67
Employment (full-time)								
Part-time employee	-0.277	-10.12	--	--	--	--	--	--
Self-employed	0.114	4.40	--	--	-0.232	-5.07	--	--
Household income (< $50,000)								
$50,000-$99,999	--	--	--	--	--	--	-0.132	-3.85
$100,000-$149,999	0.353	14.92	--	--	-0.396	-10.00	-0.692	-11.74
$150,000-$199,999	0.605	13.53	0.203	6.90	-0.396	-10.00	-0.692	-11.74
$200,000 or more	0.986	16.80	0.485	10.29	-0.396	-10.00	-0.692	-11.74
Household composition (multi-worker)								
Single person	0.362	14.50	--	--	-0.193	-4.55	--	--
Single worker multi-person	-0.171	-6.26	-0.241	-7.93	-0.435	-8.71	-0.279	-8.49
Transportation-related variables								
Residential location (rural/ suburban)								
Urban	0.363	21.64	0.413	16.35	-0.092	-2.86	-0.086	-3.43
Vehicle availability (< 1 per worker)								
= 1 per worker	--	--	--	--	-0.339	-7.58	--	--
> 1 per worker	0.059	3.79	0.144	4.06	-0.151	-3.53	--	--
Commute mode (drive alone)								
Car not-alone	-0.042	-2.00	0.053	2.04	-0.092	-2.22	0.086	2.69
Non-car	0.242	7.34	0.395	10.02	--	--	--	--
Ride-hailing experience (no)								
Private only	n/a	n/a	n/a	n/a	-0.173	-5.42	-0.420	-11.51
Pooled	n/a	n/a	n/a	n/a	-0.049	0.81	0.193	2.98
Trip attributes								
Cost [US$]	n/a	n/a	n/a	n/a	-0.294	-13.3	-0.263	-14.5
Travel time [minutes]	n/a	n/a	n/a	n/a	-0.141	-13.6	-0.102	-13.8
Additional passengers	n/a	n/a	n/a	n/a	-0.139	-8.6	-0.218	-10.0
Travel time*Time-sensitivity	n/a	n/a	n/a	n/a	-0.007	-2.0	-0.007	2.8
Travel time*IPTT	n/a	n/a	n/a	n/a	0.066	9.6	0.006	2.1
Additional passengers*Privacy-sensitivity	n/a	n/a	n/a	n/a	-0.017	-1.3	-0.073	-2.4
Constant	-0.884	-9.31	-1.214	-13.03	1.130	11.01	0.903	9.6

"--" = not statistically significantly different from zero at the 90% level of confidence and removed. "n/a" = not applicable

4.3 Private versus Shared Rides for Work and Leisure Travel

The second and third columns of Table 3 present the estimated coefficients based on the stated choice between a solo ride and a shared ride for commuting scenarios and leisure trip-purpose scenarios, respectively. There is very limited literature in the context of SAVs to which we can compare our model results. This is because, although there have been multiple studies investigating individual intentions to adopt SAVs (see for example, Zmud et al., 2016, Haboucha et al., 2017, Lavieri et al., 2017), there is little research modeling the choice between riding solo in a SAV use and sharing a ride in a SAV use. The few studies on this topic have an exclusive focus on the investigation of VTT (see for example, Krueger et al., 2016). To our knowledge, there is no current study that models WTS.

As expected, privacy-sensitivity significantly reduces the likelihood of choosing to share a ride in an SAV. The other two latent variables do not show significant direct effects after accounting for their interaction with travel time attributes (as discussed later in this section). Women and young adults exhibit a lower tendency to choose shared rides in a commuting context, but gender and age do not show effects on the decision to share trips for leisure purposes. Women are usually responsible for most household chauffeuring and shopping activities, which are usually chained with into work commutes (Buddelmeyer et al., 2017; Fan, 2017; Motte-Baumvol et al., 2017). This may explain the lower tendency of women to choose the shared ride SAV mode for the work trip. The negative inclination to use the shared ride SAV commute mode among younger adults (relative to older adults) is intriguing, especially given that younger adults are distinctly more likely to use the pooled form of ride-hailing today (as discussed earlier). It is possible that, in today's ride-hailing setting with a human driver, millennials feel somewhat more comfortable traveling with strangers because they view the human driver as a professional "guardian" during their pooled commute trips, while these same individuals (relative to their older peers) are much more wary of sharing rides in SAVs without a "guardian" human driver. There are no statistically significant direct race/ethnicity effects in the stated choice models; yet, we observe indirect race/ethnicity effects (through privacy-sensitivity and ride-hailing experience) which indicate that Non-Hispanic Whites are less likely to opt for shared rides. Individuals with graduate degrees have lower interest in sharing rides to reach leisure activities, while self-employment, compared to part-time and full-time employment, reduces the interest in sharing commute trips.

In terms of household level variables, a higher household income decreases the propensity to choose the shared ride AV mode for both activity purposes, even after accounting for indirect effects through current ride-hailing experience and beyond the indirect effects through privacy-sensitivity. This result may be an indication of the higher consumption power and a desire for personalized SAV services among higher income individuals. Finally, in the set of demographic variables, individuals living in multi-worker households (compared to living alone or in a single-worker household) are more likely to share SAV rides for both activity purposes.

The transportation-related variables also reveal intriguing effects on the stated choices of SAV services. While living in urban areas (compared to living in the suburbs or rural areas) has a significant positive association with pooled ride-hailing experience, the opposite is observed in the SAV stated choice model. This result certainly needs further investigation in the future, though it may reflect the same perception of enhanced security (as for young individuals) with a human driver present (as opposed to not having an additional individual in the form of the human driver) when traveling with strangers in and around urban areas. Household vehicle availability seems to reduce the inclination toward sharing rides for commute purposes, while not affecting leisure trip-purposes. This effect corroborates the findings of Lavieri and Bhat (2018) in the context of current pooled ride-hailing behavior in the DFW area. Next, the model shows that commuting with other individuals today reduces the interest in sharing SAV commute trips, but increases it for leisure trips. Indeed, sharing rides with strangers when already escorting family members or acquaintances may be perceived as a challenge. However, it is interesting to note that individuals who do not drive alone to work seem more open to sharing rides in situations that they would potentially be alone, such as trips to leisure activities.

Finally, the endogenous variable representing ride-hailing experience also shows very interesting effects on the stated choice outcomes. Current experience with "private ride-hailing only" (relative to having no experience with ride-hailing at all or having pooled ride-hailing experience) has a negative effect on choosing to share AVs for both activity purposes. In other words, it appears that people who have used "private ride-hailing only" appreciate the convenience and flexibility of the private arrangement based on the actual experience, and are loath to sharing the travel experience with strangers (either with current pooled ride-hailing or with pooled SAVs in the future). Particularly intriguing here is the implication that it may be easier to "convert" individuals who have never used ride-hailing into future pooled SAV users than to attempt to convince current "private ride-hailing only" users to become future pooled SAV users. From this standpoint, part-time employees appear to be a promising demographic group to court for future pooled SAV travel, given, based on our ride-hailing model results of the previous section, that they are one of the most likely groups to have never experienced ride-hailing. The fraction of part-time employees is also quite significant in today's workforce, and this fraction is only projected to increase over time (Trading Economics, 2018). Perhaps understanding their needs better (such as other household responsibilities they may shoulder) can lead to the provision of pooled ride-hailing services today as well as future pooled SAV services that can assuage their concerns about these services meeting up to their needs. On the other hand, current pooled ride-hailing users appear to be the prime segment for promoting pooled SAV use, especially for trips for leisure purposes. However, it does appear from our results that pooled SAVs are not viewed in the same light as current pooled ride-hailing use by some population segments, such as young individuals and those residing in urban areas. If this is indeed because of the comfort/security of having a human "guardian" during the trip, then it becomes incumbent that AV design pay attention to security features, such as having an emergency "911-like" button accessible to each passenger. Also, it then suggests that AV security features be advertised particularly to young individuals, high income individuals, and urban area residents to allay their anxiety toward pooled SAV travel. In any case, our results call for a deeper investigation into attitudes and perceptions associated with having a human driver versus not having one in the context of pooled ride-hailing travel. Similarly, a better understanding of why non-Hispanic Whites, in particular, shy away from pooled ride-hailing travel today can be beneficial to bringing them to the "shared-ride" fold and potentially increasing the pool of individuals who may use pooled SAVs in the future. Further, any efforts to provide additional opportunities for, and promote the use of, pooled ride-hailing today appears will have positive pay-offs for the future use of pooled SAVs. That is, there may be merit to, for example, considering the provision of deep discounts for pooled ride-hailing today (or at least for a small window of time just before the large-scale advent of AVs) as a means to attract individuals to the use of pooled ride-hailing, even if these deep discounts may not be justifiable from an economic standpoint in the short-term.

In terms of trip attribute effects and interaction effects of trip attributes and latent constructs (see toward the bottom of Table 3), all the coefficients have the expected signs. In the specific context of the interaction effects, time-sensitive individuals place a higher premium on travel time for both the work and leisure purposes, individuals with high interest in the productive use of travel time have a lower sensitivity to travel time (particularly for the work purpose), and privacy-sensitive individuals have an increasing reluctance for pooled SAV travel as the number of passengers in the shared arrangement increases (this last effect is particularly so for leisure travel). However, it is also important to note that these interaction effects generally pale in comparison to the main effects. Thus, for example, the utility difference per minute between the individual in the sample with the highest expected value of the time sensitivity latent construct and the lowest expected value of the time sensitivity construct is 1.066 (this is computed based on the SEM model predictions; the range of the expected value of the time sensitivity construct is from -0.263 to 0.803), which translates to an expected travel time sensitivity difference between these two individuals of 0.007*1.006=0.0075. This difference is less than 6% of the main travel time effect of 0.141 for the work purpose and less than 8% of the main travel time effect of 0.102 for the leisure purpose. Similar computations reveal that (a) the travel time sensitivity difference between the two individuals with the minimum and maximum expected IPTT values is 22% of the main travel time effect for the work purpose, but less than 3% of the main travel time effect for the leisure purpose, and (b) the negative additional passenger utility effect on sharing between the two individuals with the minimum and maximum expected privacy sensitivity values is about 9% of the negative valuation of the main additional passenger utility effect for the work purpose and 24% of the main additional passenger utility effect for the leisure purpose. Overall, the strongest interaction effects correspond to travel time variations due to IPTT for the work purpose, and the (dis-)utility attributable to additional passengers based on the level of privacy sensitivity for the leisure purpose.

We also tested the interaction between privacy-sensitivity and pooled SAV travel time to examine if the presence of strangers increases the disutility of time traveling, but this effect was not statistically significant. Similarly, we also tested the interaction effect of additional passengers with travel time, but again this interaction effect was not statistically significant. That is, individuals seem to have a fixed dis-utility to having a stranger travel with them, which is independent of travel time.

4.4 Model Fit Evaluation

In this section, we present the data fit results of an independent heterogeneous data model (IHDM) model that excludes the latent psychological constructs and compare this IHDM model to the proposed GHDM model. The IHDM model essentially is a set of independent models (one for each outcome, including attitudinal indicators) and ignores the jointness in the outcomes (that is, the covariances engendered by the stochastic latent constructs are ignored). The IHDM model includes the exogenous determinants of the latent constructs directly as explanatory variables as well as considers all statistically significant demographic and transportation-related variables impacting the outcome variables in the GHDM model. The GHDM and the IHDM models are not nested, but they may be compared using the composite likelihood information criterion (CLIC)[5]. The model that provides a higher value of CLIC is preferred. Another way to examine the performance of the two models is to compute the equivalent GHDM predictive likelihood value for the three main outcomes (that is, for the current revealed preference ride-hailing experience nominal variable and the repeated stated binary choice observations of SAV use (or not) for the commute purpose and the leisure purpose). The corresponding IHDM predictive log-likelihood value may also be computed. Then, one can compute the adjusted likelihood ratio index of each model with respect to the log-likelihood with only the constants. To test the performance of the two models statistically, the non-nested adjusted likelihood ratio test may be used (see Ben-Akiva and Lerman, 1985, page 172). This test determines if the adjusted likelihood ratio (ALR) indices of two non-nested models are significantly different. In particular, the test determines the probability that the difference in the ALR indices could have occurred by chance in the asymptotic limit. A small value of the probability of chance occurrence indicates that the difference is statistically significant and that the model with the higher value of adjusted likelihood ratio index is to be preferred.

We also evaluate the data fit of the two models intuitively and informally at both the disaggregate and aggregate levels. To do so, we focus on the predictions for the 12 different combinations of ride-hailing experience (three alternatives), work purpose SAV use (two alternatives), and leisure purpose SAV use (two alternatives). We then compute multivariate predictions for these 12 (=3×2×2) combinations. At the disaggregate level, for the GHDM model, we estimate the probability of the observed multivariate outcome for each individual and compute an average (across individuals) probability of correct prediction at this three-variate level. Similar disaggregate measures are computed for the IHDM model. At the aggregate level, we design a heuristic diagnostic check of model fit by computing the predicted aggregate share of individuals in each of the 12 combination categories. The predicted shares from the GHDM and the IHDM models are compared to the actual shares, and the absolute percentage error (APE) statistic is computed.

The composite marginal likelihoods of the GHDM and IHDM models came out to be –52,4983.3 and –52,9193.4, respectively. Other measures of fit are provided in Table 4a. The GHDM shows a better goodness-of-fit on the basis of the CLIC statistic, the predictive log-likelihood values and the predictive adjusted likelihood ratio indices. The same result is obtained from the non-nested likelihood ratio statistic; the probability that the adjusted likelihood ratio index difference between the GHDM and the IHDM models

[5] The CLIC, introduced by Varin and Vidoni (2005), takes the following form (after replacing the composite marginal likelihood (CML) with the maximum approximate CML (MACML)):

$$\log L^*_{MACML}(\hat{\hat{\theta}}) = \log L_{MACML}(\hat{\hat{\theta}}) - tr\left[\hat{J}(\hat{\hat{\theta}})\hat{H}(\hat{\hat{\theta}})^{-1}\right] \cdot$$

could have occurred by chance is literally zero. The average probability of correct prediction is 0.1740 for the GHDM model, and 0.1545 for the IHDM model. At the aggregate level, the shares predicted by the GHDM model are either superior to the IHDM model or about the same as the IHDM model for each of the 12 multivariate combinations. Across all the 12 combinations, the average APE is 10.69 for the GHDM model compared to 30.00 for the IHDM. The aggregate fit measures in Table 4b reinforce the disaggregate level results in Table 4a. In summary, the results show that the GHDM model proposed here outperforms the IHDM model in data fit, providing support for our modeling of the revealed preference current ride-hailing experience choice and the stated choices of future SAV use as a joint package.

Table 4a. Disaggregate Measures of Goodness-of-Fit

Summary Statistics	Model: GHDM	Model: IHDM
Composite Marginal log-likelihood value at convergence	-524,196.0	-528,710.0
Composite Likelihood Information Criterion (CLIC)	-524,983.3	-529,193.4
Predictive log-likelihood at convergence	-9,847.68	-10,133.67
Constants only predictive log-likelihood at convergence	-11,220.60	
Number of parameters	120	87
Predictive adjusted likelihood ratio index	0.113	0.090
Non-nested adjusted likelihood ratio test between the GHDM and IHDM	Φ[21.75]<<0.0001	

Table 4b. Aggregate Measures of Goodness-of-Fit

Multivariate Combination Ride-hailing experience, Leisure Purpose, Work Purpose	**Sample** Count	**Sample** Share (%)	**GHDM** Predicted Share (%)	**GHDM** APE (%)	**IHDM** Predicted Share (%)	**IHDM** APE (%)
No, Solo, Solo	675	14.00	14.69	4.93	8.60	38.55
No, Solo, Shared	343	7.11	7.22	1.50	9.92	39.46
No, Shared, Solo	294	6.10	6.59	8.06	9.86	61.69
No, Shared, Shared	791	16.41	16.01	2.40	14.69	10.49
Private, Solo, Solo	854	17.71	17.02	3.94	12.44	29.76
Private, Solo, Shared	528	10.95	11.04	0.80	12.21	11.52
Private, Shared, Solo	291	6.04	4.43	26.65	9.87	63.59
Private, Shared, Shared	574	11.91	14.43	21.21	11.91	0.01
Pooled, Solo, Solo	128	2.66	2.63	1.12	1.92	27.55
Pooled, Solo, Shared	78	1.62	1.17	27.95	2.16	33.35
Pooled, Shared, Solo	88	1.83	1.46	20.18	2.52	38.10
Pooled, Shared, Shared	177	3.67	3.32	9.59	3.89	5.89
Average APE				10.69		30.00
Average Probability of Correct Prediction			0.1740		0.1545	

5. Implications of Results

In this section, we examine the imputed values of travel time (VTT) and willingness to share (WTS) from our results, as well as discuss treatment effects and implications.

5.1 VTT and WTS Analysis

The expected values of VTT and WTS values are computed for each individual as discussed in Section 3.4. These expected values may be averaged across any demographic sub-sample or across the entire sample to obtain corresponding mean values and standard deviations. Overall, the VTT sample average estimate is $26.5 for work travel and $23.2 for leisure travel, which are rather high but may be attributed to the sample being skewed toward high-income households[6]. The higher sample average VTT for work travel compared to leisure travel is consistent with findings from previous studies (for example, Axhausen et al., 2008; Börjesson and Eliasson, 2014). Interestingly, we find a lower variation in the leisure VTT relative to the work travel VTT. In terms of the WTS estimates, the results indicate that individuals are willing to pay, on average, about 50 cents (48.71 cents is the actual point value) not to have an additional passenger for commute travel, and this willingness to pay not to have an additional passenger rises to 90 cents (89.71 cents in the actual point value) on average, for leisure travel. This is, of course, consistent with the estimation results that individuals are more sensitive to additional passengers for leisure travel relative to commute travel. As already discussed, this willingness to pay to avoid traveling with strangers represents a fixed cost, and appears to be independent of travel time. That is, the notion that individuals may be more willing to share rides for short travel times in an AV, but not long travel times, is not supported by our analysis. Another perspective on these results is that individuals are willing to pay 14% [((26.5-23.2)/23.2)x100] more to reduce a minute in a commute trip compared to a leisure trip, while they are willing to pay 84% more to avoid an additional passenger in a leisure trip compared to a commute trip. The implications of these results for transportation planning and policy are that, from a shared economy perspective, it may be easier to promote pooled SAV use for commute trips than for leisure trips. Given that commute trips are the ones that overload the system during the peak period, there may be an opportunity to alleviate some of this peak period congestion. At the same time, there does not seem to be any difference in sensitivity to riding with others in an SAV based on travel time, which suggests that promoting pooled SAV use for short-distance trips will be likely as difficult as promoting pooled SAV use for long-distance trips, both for commute and leisure travel. Still, since value of time is somewhat higher for commute trips, efforts need to be focused on minimizing delays caused by serving multiple passengers during the peak period.

A further examination of the ratios between WTS and VTT for each trip purpose provides additional insights. In particular, for commute travel, reducing one passenger in a

[6] The average household income in the sample is $125,000 and the majority of the individuals live in multi-worker households. Using the estimate of 1.7 workers per household from our sample and an average work duration of about 37 hours/week in the sample, and considering that each respondent works 52 weeks per year, a worker would earn, on average, $38.2 per hour, which means that the work-trip VTT is equivalent to 69% of the hourly wage and the leisure travel VTT is about 60% of the hourly wage rate.

commute trip has the same monetary value as reducing the travel time by 1.10 minutes. For a leisure trip, the equivalent value is 2.33 minutes. Once again, this is a fixed time cost of an additional passenger, regardless of travel time. Overall, these values are low when compared to actual delays caused by an additional passenger in a ride. Thus, our results suggest that delays are a greater barrier to pooled SAV adoption than the actual presence of strangers[7]. This result reinforces the idea that privacy concerns may not be a barrier too difficult to overcome and dynamic ridesharing may have a large market penetration potential, especially for commute trips, as long as operated efficiently with minimal detour and pick-up/drop-off delays. Of course, it is possible that the perceptions associated with the experience of sharing a ride is abstract to a large group of respondents in the sample, because of the small share of the sample that has experienced pooled ride-hailing. Thus, it may be a fruitful avenue of further research to design experiments that mimic the travel experience in a more realistic manner (using pictures or even virtual reality). Nonetheless, our results provide important insights into SAV use in the future.

5.2 Treatment Effects and Policy Implications

To examine differences in preferences for sharing among different population segments, we compute average treatment effects (ATEs) of the socio-demographic variables on ride-hailing experience and on sharing intentions in the SAV scenarios, as well as VTT and WTS. The ATE measure for the choice outcomes provides the expected difference in ride-hailing experience or SAV-service choice for a random individual if s/he were in a specific category i of the determinant variable as opposed to another configuration $k \neq i$. The ATE is estimated as follows for each determinant variable:

$$\hat{\text{ATE}}_{ikj} = \frac{1}{Q}\sum_{q=1}^{Q}\left(\left[P(y_q = j \mid a_{qi} = 1) - P(y_q = j \mid a_{qk} = 1)\right]\right) \tag{3}$$

where a_{qi} is the dummy variable for the category i of the determinant variable for the individual q, y_q stands for the choice variable, and j represents a specific choice alternative. Thus, $\hat{\text{ATE}}_{ikj}$ above represents the estimate of the expected value change in the nominal category j of the choice outcome because of a change from category k of the determinant variable to category i of the determinant variable. In computing this effect, we first assign the value of the base category for each individual in the sample (that is, we assign the value of $a_{qk} = 1$ to the determinant variable of each individual to compute $P(y_q = j \mid a_{qk} = 1)$) and then change the value of the variable to $a_{qi} = 1$ compute $P(y_q = j \mid a_{qi} = 1)$).

In our analysis, we compute the ATE measures for only two categories of the determinant variables. The base category for each determinant variable is used as the category to change from (as denoted by index k in Equation (3)) and a single non-base category of the determinant variable is selected as the category to change to (as denoted by index i in Equation (3)). For example, in the case of age, the base category is the “≥65 years” age

[7] Note that from an experimental design perspective, the range of additional time per individual varied from 1.66 to 10 minutes. Our results regarding the equivalent time value of an additional passenger is at the bottom of this range.

group, while the changed category corresponds to the "18-34 years" age group. Similarly, for race/ethnicity, the base category is the "other" race/ethnicity (including individuals of Hispanic and non-White races) and the changed category is the "non-Hispanic White" race/ethnicity. We follow the same process of comparing a base and a non-base category of the determinant variables to evaluate percentage changes in VTT and WTS for the two trip purposes investigated. The results are presented in Table 5. Using employment type as an example, the ATE effect of -0.08 on private ride-hailing experience is interpreted as follows: if 100 random individuals moved jobs from full-time employment to part-time employment, there would be 8 fewer individuals with private ride-hailing experience.

The results in Table 5 indicate that high-income individuals, millennials, and individuals who live alone are the segments most likely to adopt private ride-hailing, while lower income millennials, individuals living in multi-worker households and individuals who are not non-Hispanic Whites are the most likely to have experience with pooled ride-hailing. Overall, age and income are the strongest predictors of ride-hailing experience and sharing intentions. As discussed earlier, millennials are more likely than those 65+ years of age to adopt pooled ride-hailing today, but are also more reluctant to indicate intent to use pooled SAVs in the future. Millennials also have a higher WTS value relative to those 65+ years of age, indicating an aversion to sharing rides in SAVs. Why these results are so is an important avenue for further research, especially because millennials just became the majority of the population in the U.S. and the success of SAVs and MaaS are critically dependent on this segment's adoption.

Although individuals living in high-income households are the most likely to use private ride-hailing services, they demonstrate high sharing aversion in all dimensions. An interesting and worrisome result is that the interest in the productive use of travel time for work travel reduces travel time disutility for this group, which then tempers the higher time-sensitivity of this group. The net result is that there is no statistically significant difference in VTT between the low and high income categories for work travel (and the difference in VTT is rather marginal even for leisure travel), as may be observed in the VTT percentage change columns for the income row in Table 5. With reduced VTT, high sharing aversion and high economic power, these individuals may have significant increase in "ride-alone VMT" when AVs become available. Encouraging high-income individuals to share rides will be challenging, but could be encouraged by upscale services offering additional comfort features for a higher price.

Transferring individuals from rural and suburban environments and encouraging commute by non-car modes instead of drive alone shows a positive impact on both private and pooled ride-hailing experience. In fact, together with age, both living in an urban area and commuting by a non-car mode are the strongest positive predictors of pooled ride-hailing. Yet, similar to millennials, despite the experience with pooled ride-hailing, urban residents seem less interested in sharing rides in SAVs for both work and leisure purposes. From an operational perspective, urban (dense) areas are the most suitable environment to the efficient operation of dynamic ridesharing (because the demand is concentrated and thus matching becomes easier), thus further investigation of this negative effect observed herein is necessary.

Table 5. Treatment Effect of Socio-Demographic Variables on Main Outcomes, VTT and WTS Based on Model 3

Variable	Categories Compared (base versus changed)	Change in Probability								Percentage Change							
		Ride-hailing experience				Work purpose		Leisure purpose		Work purpose				Leisure purpose			
		Private only		Shared		Shared		Shared		VTT (%)		WTS (%)		VTT (%)		WTS (%)	
		Est.	St. err	Est.	St. err	Est.	St. err.	Est.	St. err.	Est.	St. err.	Est.	St. err.	Est.	St. err.	Est.	St. err.
Gender	**Male vs. female**	--	--	--	--	-0.032	0.006	-0.006	0.003	1.029	0.217	--	--	1.255	0.264	--	--
Age	**65+ vs. 18 to 34**	0.316	0.026	0.049	0.006	-0.021	0.008	-0.102	0.015	-16.221	3.436	2.069	1.373	-1.891	0.398	5.487	3.634
Race	**Other vs. Non-Hispanic White**	0.021	0.004	-0.040	0.007	-0.028	0.006	-0.040	0.008	--	--	1.616	0.410	--	--	4.291	1.070
Education	**< bachelor's vs. graduate**	0.007	0.003	-0.002	0.001	0.028	0.007	-0.015	0.006	-6.614	1.663	--	--	-0.764	0.191	--	--
Employment	**Full-time vs. part-time**	-0.080	0.009	0.021	0.003	0.011	0.004	0.020	0.006	-2.177	0.445	--	--	-2.652	0.539	--	--
Income	**< $50,000 vs. $200,000+**	0.337	0.019	-0.023	0.006	-0.269	0.029	-0.133	0.015	--	--	4.288	0.765	1.565	0.554	11.266	1.947
Households composition	**Multi-worker vs. single-worker**	0.137	0.011	-0.032	0.003	-0.034	0.007	-0.013	0.002	--	--	--	--	--	--	--	--
Residential location	**Rural/suburban vs. urban**	0.098	0.007	0.042	0.004	-0.027	0.005	-0.017	0.004	--	--	--	--	--	--	--	--
Vehicle availability	**< 1 per worker vs. > 1 per worker**	0.008	0.005	0.021	0.006	-0.025	0.007	--	--	--	--	--	--	--	--	--	--
Commute mode	**Drive alone vs. Non-car**	0.049	0.008	0.051	0.007	--	--	--	--	--	--	--	--	--	--	--	--
Ride-hailing experience	**No vs. Pooled**	n/a	n/a	n/a	n/a	-0.008	0.008	0.039	0.009	--	--	--	--	--	--	--	--

"--" = not statistically significantly different from zero at the 90% level of confidence.

6. Conclusions

There is growing evidence that ridesharing will be a key element to ensure a sustainable future to urban transportation in an AV future. In this context, the current paper proposed and applied a multivariate modeling framework to investigate the extent to which individuals are willing to share rides with strangers in a SAV future. A joint model of current ride-hailing experience and stated intentions regarding the use of shared rides for trips to work and to leisure activities was estimated and VTT and WTS (money value of traveling alone compared to riding with strangers) were computed for each individual in the sample. The model relied on three stochastic psychosocial latent constructs representing privacy-sensitivity, time-sensitivity and interest in productive use of travel time to create dependency among the three nominal outcomes and to moderate the effects of trip attributes (time and number of additional passengers) for each individual.

The use of psychosocial latent constructs as a key component in our model provides important insights regarding transportation planning and policy. First, we identified that privacy concerns are currently discouraging individuals (mostly non-Hispanic Whites) from experimenting pooled ride-hailing services, and such concerns also create a significant aversion to future pooled SAV services, which can be deterring to the idea of MaaS in currently car-dominated cities. Privacy-sensitivity may also be worsened by security concerns in a SAV context where individuals see themselves alone with a stranger in the vehicle (since there is not a driver to serve as a "professional guardian" during the trip). Although we did not investigate security concerns directly, we did observe that current pooled ride-hailing users may be reticent to using shared rides in a SAV, which could be preliminary evidence of this issue. Hence, a comprehensive examination of privacy and safety concerns of current pooled ride-hailing users may be a necessary step to prevent this group from moving to private rides as SAVs become available. Social-network-based ridesharing schemes can be an interesting solution to privacy and security concerns in shared rides. This type of scheme has been recently proposed and simulated from a supply standpoint, but is still to be implemented (see Richardson et al., 2016, and Wang et al., 2017). In that sense, MaaS-oriented travel behavior research efforts can help investigate consumer's interest and potential demand to this new type of service. Second, the latent variable representing the interest in productive use of travel time provided evidence that this is an important factor currently guiding ride-hailing adoption. Considering the current interest by transportation researchers in understanding the impacts of automation on VTT, the evidence obtained in the current study is very important. Ride-hailing services can be an important proxy SAV services and can provide valuable data to measure potential changes in individual's VTT due to productive use of travel time (even as a tool for naturalistic experiments). We also observed that providing an environment that is conducive to productive use of travel time may increase high-income individual's tolerance to increased travel times, which may incur in increased transportation equity problems. High-income individuals are currently the main users of private ride-hailing and demonstrate high sharing aversion in all dimensions. Thus, if their VTT decreases due to productive use of travel time, they may have a disproportional increase in "ride-alone VMT". Encouraging high-income individuals to share rides will be challenging and calls for future research. Yet, this group could be encouraged to share if upscale services are offered within MaaS packages.

Third, we observed that when dealing with individuals who are intrinsically privacy and time-sensitive, an environment that is conducive to the productive use of travel time will have little to no effect on increasing their tolerance to increased travel times and/or additional passengers. This indicates that despite the potential of automation in reducing VTT, there are population segments that are unlikely to become less time-sensitive, such as full-time employed women between the ages of 35 and 44 years old.

In terms of actual measures of VTT and WTS, our results point to the importance of distinguishing trip purposes. For instance, individuals seem to be less sensitive to the presence of strangers in a commute trip than in a leisure trip, but the sensitivity to time is the opposite. The implications of these results for transportation planning and policy are that, from a shared economy perspective, it may be easier to promote SAV use for commute trips than for leisure trips. Given that commute trips are the ones that overload the system during the peak period, there may be an opportunity to alleviate some of this peak period congestion. At the same time, there does not seem to be any difference in sensitivity to riding with others in an AV based on travel time, which suggests that promoting SAV use for short-distance trips will be likely as difficult as promoting SAV use for long-distance trips, both for commute and leisure travel. Still, since value of time is somewhat higher for commute trips, efforts need to be focused on minimizing delays caused by serving multiple passengers during the peak period. A further examination of the ratios between WTS and VTT reinforced the idea that privacy concerns may not be a barrier too difficult to overcome and dynamic ridesharing may have a large market penetration potential, especially for commute trips, as long as operated efficiently with minimal detour and pick-up/drop-off delays. This result points to a potential bright future for pooled SAV based MaaS systems in car-dominated environments.

The current study is just a first step to an important travel behavior topic. A similar framework to the one proposed herein can be enhanced by the inclusion of a fourth latent variable representing individuals' sensitivities to travel monetary costs. As largely discussed in the VTT and WTP literature, accommodating variability in the cost coefficient is important to avoid erroneously attributing variation to WTP. Additionally, a new experimental design that captures individuals current VTT would allow the identification of biases in the values estimated in this study.

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