

**Pooled Versus Private Ride-Hailing: A Joint Revealed and Stated Preference Analysis
Recognizing Psycho-Social Factors**

Shuqing Kang

The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin TX 78712, USA
Email: kangshuqing@utexas.edu

Aupal Mondal

The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin TX 78712, USA
Email: aupal.mondal@utexas.edu

Aarti C. Bhat

The Pennsylvania State University
Department of Human Development and Family Studies
405 Biobehavioral Health Building, State College PA 16802, USA
Email: acb6009@psu.edu

Chandra R. Bhat (corresponding author)

The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin TX 78712, USA
Tel: 1-512-471-4535; Email: bhat@mail.utexas.edu
and
The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong

ABSTRACT

Pooled mobility services hold substantial promise as a means to provide better accessibility to those who may find it difficult to drive themselves, while also promoting sustainable transportation efforts. In this paper, we develop a joint revealed preference-stated preference model for the choice between pooled versus private ride-hailing that (a) accommodates a suite of individual-level socio-demographics, individual-level psycho-social attributes, built environment variables, and trip-level variables, and (b) explicitly recognizes the importance of considering familiarity with pooled ride-hailing (RH) as an integral element of the pooled RH choice process. The primary source of data for the analysis is drawn from a 2019 survey of Austin, Texas residents. Our results underscore the value of using psycho-social latent constructs in the adoption of current and emerging mobility services, both in terms of improved prediction fit as well as in terms of designing proactive strategies to promote pooled RH service adoption. Women, older adults, and non-Hispanic/non-Latino Whites have a low propensity to choose the pooled RH mode, while employed individuals, highly educated individuals, and those living in high density urban areas have a high propensity. Overall, the average VTT estimate is \$27.80 per hour for commute travel, \$19.40 per hour for shopping travel, and \$10.70 per hour for leisure travel, while the willingness to pool (that is, the willingness to pay to not pool a ride or WTS) averages about 62 cents for commute travel, \$1.70 for shopping travel and \$1.32 for leisure travel. These estimates can be used by TNCs and cities to consider new integrated pooled RH-fixed transit service designs, position traffic congestion alleviation strategies and new mobility services, and customize information campaigns to promote pooled RH mode use.

Keywords: joint RP-SP analysis, psycho-social factors, ride-hailing, pooled mobility, willingness-to-share, value of travel time.

1. INTRODUCTION

App-based ride-hailing (RH) services have grown in popularity over the past decade, in large part because these mobility services offer the same kind of convenient door-to-door transport and travel time efficiencies as does the private car (Dias *et al.*, 2017). Such RH services, provided by what are now labeled as Transportation Network Companies (or TNCs) (such as Uber, Lyft, Ola, and Didi), offer enhanced transportation accessibility to many sections of the population (including those who are physically challenged to drive and those who do not own a personal vehicle, but need door-to-door transport for occasional trips; see Leistner and Steiner, 2017 and Lavieri *et al.*, 2018). RH services are also being credited for reducing crashes involving intoxication, because they can be conveniently summoned after a late night of socialization (see Garikapati *et al.*, 2016; Lavieri and Bhat, 2019a). Further, as the transportation sector enters into a new era of substantial and (eventually) full vehicular automation, it is expected that there will be a convergence of RH services with autonomous vehicles (see Hyland and Mahmassani, 2020; Narayanan *et al.*, 2020). Thus, RH usage is only likely to grow further in the near future (Gerte *et al.*, 2018).

Despite the numerous social advantages of modern RH services, there are traffic-related externality concerns too that arise with their increasing adoption. Recent studies (see, for example, Lavieri and Bhat, 2019a; Wenzel *et al.*, 2019; Nair *et al.*, 2020) indicate that new trips generated on weekdays by RH are more likely to occur in urban areas, and are more likely to be made during the morning commute period. Such trips can add to peak period traffic congestion as well as traffic crashes (the morning commute period is a traffic crash-prone period of the day; see Paleti *et al.*, 2010). Further, there is evidence that RH services have drawn mode share away from public transportation and active transportation modes (walking and bicycling) (Lavieri and Bhat, 2019a; Tirachini, 2020; Tirachini and del Rio, 2019). In addition, there is the increased vehicle miles of travel (VMT) due to deadheading trips or empty trips. These are trips that are made by RH vehicles when there are no passengers in the vehicle. The above considerations have led some to argue that RH is at least partially responsible for the worsening traffic congestion in a number of cities (Schaller, 2017; LeBlanc, 2018; Erhardt *et al.*, 2019). Of course, an important reason for the negative consequences of RH has been that most RH trips are taken by a single individual (Henao and Marshall, 2019; Lavieri and Bhat, 2019a). While TNCs initiated a pooled version of their services (labeled, for example, as UberPOOL or LyftShare) in many U.S. cities, the uptake of such pooled RH services has been rather low. This is despite the fact that pooling can lead to a lower cost for consumers, and combines the merits of ease-of-use, door-to-door, and on-demand service. The reluctance to use the pooled version of RH has been attributed to the increased time delays caused by sharing rides and to the general reticence to pool rides with strangers (see Lavieri and Bhat, 2019b; Alonso-González *et al.*, 2020a).

An important question that arises then is whether there are ways that pooling can be encouraged within the context of information and communications technology (ICT)-based RH services. On the surface, it would seem that such services offer a level of convenience and security that should make pooling rides easier than with traditional car-pooling mechanisms (where an individual involved in the pooling arrangement drives to pick-up/drop-off others, and matching is

done using non-ICT methods and has to be pre-planned). In fact, earlier research suggests that pooled on-demand RH services can be offered with very little extra travel time for users, because of the efficient ICT-based dynamic matching protocols used by TNCs (Tachet *et al.*, 2017). From a system performance perspective, simulation studies also have shown that pooling can improve the performance of RH services at an overall macro-level (Liang *et al.*, 2020), and that pooled RH holds the key to reduced system-level VMT and urban air quality improvement (Martinez and Viegas, 2017; ITF, 2017; Tirachini and Gomez-Lobo, 2020). However, an important caveat is that all these results are predicated on a relatively high pooled RH demand penetration rate in the first place, in a kind of a “chicken-and-egg” loop. In other words, to make pooled RH increasingly more attractive, there is a need to attract individuals to pooled RH in the first place.

From a research standpoint, the above discussion points to a need to better understand the facilitators and deterrents to pooled RH use, which is the focus of the current paper. We use a combination of revealed preference (RP) data as well as stated preference (SP) data to tease out the effects of a comprehensive set of determinant factors, including socio-demographics, subjective attitudes and lifestyle characteristics, built environment variables, and trip-level attributes. A multivariate RP-SP model is estimated. Based on the model results, we propose policy actions that can help encourage the uptake of pooled RH systems. The primary source of data is an Austin area survey undertaken by the authors from July to October 2019.

The rest of this paper is organized as follows. Section 2 provides a brief overview of past literature on RH, with an emphasis on pooled RH. Section 3 presents the research method, which includes the description of the conceptual framework, the data collection design, and the model methodology. Section 4 describes the sample characteristics, while Section 5 presents the model results and goodness of fit measures. Section 6 discusses the practical implications of our findings. Finally, Section 7 concludes by summarizing important results and briefly identifying future research directions.

2. LITERATURE OVERVIEW AND THE CURRENT STUDY

There is an increasing body of literature investigating the motivations and barriers to RH adoption and frequency of use (see Tirachini, 2020 for an extensive recent review). These earlier studies have provided important insights on the individual-level, trip-level, and built-environment attributes affecting RH adoption in general. However, research focused on the distinction between private RH (RH alone with a driver) and pooled RH (RH with one or more other passengers), the focus of this paper, has been comparatively sparse. There are at least two reasons for this. The first is that pooled RH is still not available in many cities and is a more recent introduction compared to private RH, even in cities where pooled RH exists currently. The second is that there is little available data from revealed choices to model pooled RH, because, even if such a service exists, its usage has been very low. Indeed, that is the reason why the few studies of pooled RH have typically used a stated preference element to elicit preferences. Even so, the important role that pooled RH can play in shaping a sustainable transportation future has not gone un-noticed, spurred

by recent studies that extol the virtues of promoting pooled RH (Schwieterman and Smith, 2018; Alonso-Mora *et al.*, 2017).

Of the studies examining pooled RH, a first category of studies has focused on the propensity to consider pooled RH, without expressly investigating the choice between private RH and pooled RH (see, for example, Alonso-González *et al.*, 2020b; Spurlock *et al.*, 2019; Lo and Morseman, 2018). A second category of studies expressly investigates the choice between private RH and pooled RH. This group of studies is of direct relevance to this study. Interestingly, all the five studies in this second category have been published within the past year, as discussed below.

Tirachini and del Rio (2019) examine the use of RH in Santiago de Chile using a 2017 intercept (face-to-face) RP survey. One small component of their analysis corresponds to the vehicle occupancy rate of RH trips. Only trip purpose and household income are included in their specification to explain vehicle occupancy. The results indicate that pooled RH is less likely to be adopted for leisure trips and by individuals with a high income. Attitudinal variables, built environment attributes, and trip-level characteristics (other than trip purpose) are not considered.

Lavieri and Bhat (2019a) examine the choice of private versus pooled RH using an online survey of residents of the Dallas-Fort Worth Metropolitan Area. The analysis is based on individuals who have ride-hailed in the past, and the information on private versus pooled RH is sought in the context of the most recent RH trip. A suite of socio-demographic and psycho-social attitudinal/life style characteristics, as well as a macro-representation of residential location (urban versus suburban versus rural residence), is considered in their RP analysis. The main deterrents to pooled RH adoption, according to their results, are low residential location density and people's privacy concerns. In addition, tech-savviness, being young, and a high education status are associated with a higher pooling propensity. The study does not consider trip-level attributes.

Hou *et al.* (2020) use newly available Chicago TNC network data to examine RH trips between pairs of Chicago census tracts. The dependent variable in their study is the number of individuals indicating a willingness to pool as a proportion of the total number of RH trips between any two tracts (within each 15-minute time bin). The TNC network data is combined with supplementary area-level demographic and weather data. The independent variables include trip-specific attributes, temporal and weather characteristics, and area demographic and density attributes. Airport drop-offs, drop-offs at locations with high median household income, and weekend trips are most likely to be pursued using the private RH mode rather than in the pooled RH mode. The nature of the data used precludes the use of individual-level explanatory variables.

The two studies that are most closely associated with the current study are those by Lavieri and Bhat (2019b) and Alonso-González *et al.* (2020a).

Lavieri and Bhat (2019b) examine pooling adoption in the context of individuals' acceptance of increased travel times associated with pick-up/drop-off of other passengers, travel costs, and their approval of strangers sharing the same vehicle. They use joint RP-SP survey data obtained through a web-based survey of commuters in the Dallas-Fort Worth Metropolitan Area (DFW) of the U.S. A multivariate approach is used to simultaneously model individual's current RH experience and their future intentions regarding the use of shared autonomous vehicle (SAV)

and pooled SAV (PSAV) services for commute and leisure trip purposes (SAV services are essentially private RH services without a human driver, while PSAV services are essentially pooled RH services without a human driver). To accommodate individual variability in the valuation of privacy and time, Lavieri and Bhat use the attitudinal/lifestyle constructs of privacy-sensitivity, time-sensitivity, and interest in productive use of travel time (IPTT). Privacy-sensitivity yet again features as one of the most important deterrents for pooled RH. The results also reveal that users are less sensitive to the presence of strangers when in a commute trip compared to a leisure-activity trip. This is perhaps the first study to consider the full comprehensive set of individual-level variables, attitudinal/lifestyle preferences, built environment (albeit in the form of a coarse urban versus suburban residence distinction), and trip-level attributes. However, the effects of trip-level attributes on the willingness to share trips is obtained based on an SAV system in the future rather than on a human-driven RH system. Also, the level of familiarity with RH is not considered as an element of the modeling process, which can bias trip-level effects (as discussed in the next section).

Alonso-González *et al.* (2020a) use a pure SP approach primarily to investigate the use of pooled RH in the future. This study has many similarities with Lavieri and Bhat (2019b), even though it is undertaken in a very different geographical context. Also, the approach introduces socio-demographic variations based on a combination of covariate effects and latent segmentation effects, while Lavieri and Bhat (2019b) introduce socio-demographic effects based on a combination of covariate effects and psycho-social mediation effects. Remarkably, despite differences in survey methodology, model specification, and geographic contexts, this study and that of Lavieri and Bhat (2019b) find similar magnitudes for the implied money value of time of the order of \$25 per hour. The willingness to pay to not share a ride (WTS) from both studies is of the order of 50 cents to 90 cents per additional passenger. The Alonso-González *et al.* (2020a) study, however, does not include attitudinal considerations. Like Lavieri and Bhat, it also forces respondents to make a choice of private versus pooled RH, regardless of whether they have any familiarity with RH services or not.

2.1. The Current Study

This study contributes to the literature by examining the choice between private and pooled RH. There are many salient features of the study. First, we consider both RP and SP data in the analysis. While RP data (in our study, whether private or pooled RH was used in the most recent RH trip) provides a realism “anchor” in model estimation and application, the nature of RP data makes it difficult to obtain precise parameters characterizing behavior (due to inadequate observed variation in, and high correlation among, exogenous variables of interest, such as times and costs). Besides, the number of individuals selecting pooled RH is typically very low from RP data. SP data provides the opportunity to vary costs, times, and the number of passengers in a controlled manner, avoiding multi-collinearity and allowing better trade-off analysis. In combination, RP and SP data allow the analyst to harness the advantages of each type of data where the other falls short (Wardman, 1988; Ben-Akiva and Morikawa, 1990; Bhat and Castelar, 2002). To our knowledge, this is the first

study using both RP and SP data to model private versus pooled choice within the context of a human-driven RH system. Second, we explicitly consider an individual's familiarity with pooled RH, because any policy intended to enhance the propensity to pool RH rides is contingent on first ensuring that a person is familiar with pooled RH (as expected, all the individuals familiar with pooled RH were also familiar with private RH). Also, earlier literature in the socio-technical adoption literature has clearly established the importance of awareness/familiarity with a technology on technology use (see Piao *et al.*, 2016; Ward *et al.*, 2017; Marikyan *et al.*, 2019). Thus, the choice between the private and pooled RH alternatives in the RP and SP contexts is modeled based on only those who are familiar with pooled RH (for ease of presentation, we will refer to this dimension of choice as "pooled RH familiarity"; the precise way that we characterize "pooled RH familiarity" is discussed in Section 3.4). However, important to note is that we consider pooled RH familiarity jointly with the choice between the pooled and private RH alternatives. That is, we recognize that there are likely to be individual personality traits (such as green lifestyle propensity or sharing propensity) that make a person more likely to be both familiar with pooled RH service and also select pooled service in the RP and SP choices (this issue is commonly referred to as "self-selection" in the econometric literature; ignoring this self-selection will generally lead to biased and inconsistent estimates in the pooled versus private RH choice). Third, we consider a complete suite of socio-demographic variables, attitudinal/lifestyle (or psycho-social) characteristics, built environment attributes, and trip-level variables in our model. Based on earlier studies, the psycho-social characteristics (introduced as latent constructs) include tech-savviness, sharing propensity, and a green lifestyle. Also, our consideration of built environment variables goes beyond macro-level representations based on density, and includes additional variables such as land-use mix, public transit accessibility, and road network density. Fourth, we use a multivariate approach to simultaneously model the following outcomes of interest: (1) Pooled RH familiarity (a binary choice), (2) the RP choice of private versus pooled RH (a binary choice), (3) The SP choice of private versus pooled RH for the commute purpose (a binary choice), (4) The SP choice of private versus pooled RH for the shopping purpose (a binary choice), and (5) The SP choice of private versus pooled RH for the social/leisure purpose (a binary choice; in the rest of this paper, we will use the term "leisure" for this social/leisure purpose). In this context, the latent constructs of tech-savviness, sharing propensity, and green lifestyle not only help capture important emotive effects, but also serve as vehicles to allow the parsimonious joint modeling of the RH behavioral choices (that is, the five main outcomes of interest). The modeling methodology is a special case of Bhat's (2015) Generalized Heterogeneous Data Model, as detailed in Section 3.6. Fifth, we develop an approach to combine the RP and SP results to obtain an integrated RP-grounded trip purpose-specific choice model that then is used to translate the results to managerial insights for policy making. This is achieved by partitioning the influence of an exogenous variable into a direct effect and also indirect mediating effects through the psycho-social constructs, which enables the identification of effective targeting and positioning strategies, customized to each socio-demographic group of the population.

3. METHOD

3.1. Conceptual Framework

The conceptual framework is presented in Figure 1. Exogenous socio-demographic and built environment variables (left side of the figure), and three latent constructs (also referred to as psycho-social variables in the rest of this paper) representing technology savviness, sharing propensity, and green lifestyle propensity (middle of the figure), serve as determinants of the five endogenous variables of interest (pooled RH familiarity, the RP choice of private versus pooled RH, and the three SP choices of private versus pooled RH for the commute, shopping, and leisure purpose). The relationship of the exogenous variables with the latent constructs constitutes the structural equation model (SEM) component of the model (the left side of Figure 1). Specifically, as illustrated in Figure 1, the SEM component defines each latent construct (represented as ovals in the middle panel of the Figure) as a function of exogeneous socio-demographic variables and an unobserved random error term (denoted by η_1, η_2 , and η_3). Each error term represents the effect of unobserved individual factors on a specific latent construct. Of course, the presence of these error terms render the latent constructs stochastic. Also, the SEM model relationship between the socio-demographic variables and the latent constructs, as well as the correlation matrix of the three error terms, are not directly estimable, but are estimated through observations on the latent construct indicators (not shown in Figure 1 to avoid clutter, but see Section 3.3 for a discussion of these attitudinal indicators and Figure 3 for descriptive statistics of these indicators). The relationship of the latent constructs with the attitudinal indicators, and the relationship of the three latent constructs and exogenous variables with the main outcomes, constitute the MEM component of the model (the right side of the figure).

3.2. Exogenous Variables

We consider socio-demographics and a comprehensive list of built environment variables as exogenous variables. The socio-demographic variables include gender, age, race/ethnicity, education and employment status, household tenure (own or rent home), and household income. The built environment (BE) variables correspond to the respondents' home locations, and are developed by geocoding reported residential locations to Census Block Groups (CBGs). Next, seven attributes corresponding to each respondent's residential CBG are appended to the individual's record: population density (people/acre), employment density (jobs/acre), land use mix index based on five sectors of employment (retail, office, industrial, service, entertainment), street network density (links/acre), distance to nearest transit stop (meters from the centroid of CBG to the nearest transit stop), transit access (whether the distance to the nearest transit is less than/equal to 3/4 of a mile or over), and living environment (urban, suburban, or rural).^{1,2} All

¹ The land-use mix index is a continuous variable between 0 and 1, as obtained from the U.S. Environmental Protection Agency (U.S. EPA) Smart Location Database. This index is computed using an entropy approach (see Ramsey and Bell, 2014 for details).

² The living environment characterization is determined based on activity density, which represents the total number of jobs and dwelling units per unprotected acre for each CBG. Based on Ramsey and Bell (2014), CBGs with an

variables are continuous variables, except the transit access variable (dummy) and the living environment variable (categorical). We tested all these variables within the model in both continuous form and dummy variable form. At the end, only three of these variables turned out to be statistically significant in the model system, all in a dummy variable form. These variables are living environment (rural versus non-rural), transit access, and population density (high versus not-high; a population density value of more than 20 individuals per acre is characterized as high population density). These are the three BE variables listed in Figure 1.

In addition to the socio-demographic and BE variables, trip-level attributes in the SP scenarios also serve as exogenous variables (see top right of Figure 1). Indeed, the particularly attractive feature of our analysis is that we are able to estimate both individual-level as well as trip-level attribute effects on the choice of pooled versus private RH. The trip-level attributes considered in our SP scenarios include two attributes for each of the pooled and private RH options: travel time and travel cost. In addition, the number of additional passengers was a third attribute specific to the pooled RH option. Further details of the SP experimental design are provided in Section 3.5.

3.3. Latent Constructs

Recent transportation research has drawn attention to the fact that short-term mobility-related choices are not only a function of socio-demographics and longer term BE variables, but also affected by attitudes and lifestyle preferences. Accordingly, our model includes unobserved latent constructs that capture individuals' psycho-social preferences. In the context of pooling, three latent constructs (tech-savviness, sharing propensity, and green lifestyle propensity) are identified in this study based on earlier studies in transportation (see, for examples, Lavieri *et al.*, 2017; Lavieri and Bhat, 2019b; Li and Kamargianni, 2020) as well as in the more general ethnography field in the context of sharing behavior (see, for example, Wang and Jeong, 2018; Ryu *et al.*, 2003; Hu *et al.*, 2019).³ Each latent construct has three to five indicators, with responses obtained to these indicators (in the form of attitudinal statements) on a five-point Likert scale of “strongly disagree”, “somewhat disagree”, “neutral”, “somewhat agree”, and “strongly agree”.

The first latent construct, tech-savviness, captures an individual's generic inclination toward, and adeptness at, using technology. This latent construct has been widely employed in the emerging urban mobility research literature (see, for example, Alemi *et al.*, 2018; Velázquez Romera, 2019; Lavieri and Bhat, 2019b; Asmussen *et al.*, 2020), because many of the emerging mobility services require the use of a smartphone app as well as require a certain degree of acceptance of technological change. Four attitudinal statements are used as indicators for tech-savviness:

activity density less than 0.5 activity units per unprotected acre of land are classified as rural, while those with activity densities higher than 6 units per unprotected acre are classified as urban; all other CBGs are classified as suburban.

³ Other latent constructs for security concern and time sensitivity were also developed and tested, but did not turn out to provide any substantial gains in explaining the main outcomes. In part, this is because of correlation between these constructs and the constructs considered in this paper. For example, the indicators for security concern and sharing propensity were quite similar in our factor loadings.

- I like to be among the first to have the latest technology.
- Learning how to use new technologies is often frustrating for me (inverse scale).
- Having internet connectivity everywhere I go is important to me.
- I like trying things that are new and different.

The second latent construct, sharing propensity, relates to the propensity of an individual to share services and information. This construct includes a combination of the general discomfort in being with strangers, especially in enclosed spaces, as well as the extent to which an individual would like to not share (that is, protect) personal information, location information, and travel logs (which may be of particular concern when traveling with other individuals in the same pooled ride). While we attempted to distinguish between the former personal safety concerns/discomfort in being with strangers from the latter more security-related concerns, the best specification was obtained by combining these two into a single construct. Interestingly, though, the latent construct loaded much more on the personal safety concerns/discomfort indicators, suggesting that sharing behavior is more dictated by the willingness to share the service and less so by the unwillingness to share information. Indeed, earlier studies have also identified the (un)willingness to share services as one of the most significant factors that discourages people from using pooled RH (Alonso-González *et al.*, 2020a; Lavieri and Bhat, 2019b). Indicators for this second latent construct, with negative loadings of the construct, include:

- I feel uncomfortable around people I do not know.
- Traveling with a driver I don't know makes me feel uncomfortable.
- For shared ride-hailing (*e.g.*, UberPOOL, LyftShare), traveling with unfamiliar passengers makes me uncomfortable.
- Sharing my personal information or location via internet-enabled devices concerns me a lot.
- I am concerned that my travel logs and personal information stored in AVs could be leaked.

The last latent construct is green lifestyle propensity (GLP), representing an individual's preference for making daily life decisions to minimize the negative effect of one's action on our natural environment. As a widely used latent construct in travel behavior studies, GLP has been found to have a strong and positive link with the use of traditional pooling modes (such as transit; see Lee *et al.*, 2020) and RH (Alemi *et al.*, 2018; Lavieri and Bhat, 2019a). This latent construct is expected to have a positive impact on the willingness to pool a RH ride. The three attitudinal statements used to characterize GLP include:

- The government should raise the gas tax to help reduce the negative impacts of transportation on the environment.
- I am committed to an environmentally-friendly lifestyle.
- I am committed to using a less polluting means of transportation (*e.g.*, walking, biking, and public transit) as much as possible.

3.4. Main Outcome Variables

The main outcome variables in this model include five binary variables, listed on the right side of Figure 1. The first outcome is pooled RH familiarity, which is represented by whether an individual is familiar with pooled RH service. To be precise, the original question in the survey was: “How often do you generally use the following transportation services?” Each respondent was asked to answer this question separately for private RH and pooled RH. The response categories included the following:

- (1) I am not familiar with it
- (2) I am familiar with but never use the service
- (3) I am familiar with, but use it rarely (e.g. less than once a month)
- (4) I am familiar with, and use it monthly
- (5) I am familiar with, and use it weekly

In this paper, an individual is assumed to be ‘familiar with’ a service if the person selects response categories (3) (4) or (5). Essentially, our characterization of familiarity combines the notions of familiarity and actually experiencing the service at least once (that is, first-use). Of course, as expected, in our sample, any individual who is familiar with pooled RH service is also familiar with private RH, but the reverse is not the case. Thus, we consider only pooled RH familiarity (and not private RH familiarity too). Of the 953 individuals in our sample (see discussion later in Section 4), 359 (about 38%) indicated familiarity with the pooled RH service, and we model the choice between the pooled and private RH services for the “most recent trip” in the RP choice context only for these 359 individuals. The importance of considering pooled RH familiarity separately from the choice of pooled versus private RH binary choice cannot be overstated. While it may seem that one can as well eschew the modeling of familiarity and consider all the 953 individuals in the binary model of pooled versus private RH use for the most recent RH trip, there are multiple reasons not to adopt this approach. From an econometric perspective, simply including all individuals in the pooled versus private RH choice has the effect of increasing the fraction of individuals who will be observed to select the private RH alternative, and the skewed distribution (toward private RH) will result in increasing the variance of coefficient estimates. In addition, the fundamental motivation and factors affecting the familiarity/first-use state can be quite different from the preference structure characterizing the choice of pooled versus private RH for a specific RH trip. If a single preference structure is incorrectly enforced for both the familiarity and the choice decisions, the result, in general, will be biased choice model estimates, leading to incorrect sensitivity to variable changes and poor policy/forecasting performance; see, for example, Shocker *et al.* (1991), Williams and Ortuzar (1982), Swait and Ben-Akiva (1987), Basar and Bhat (2004), and Bhat (2015). As an example, in our empirical results later, we find that older individuals are less likely to use the pooled RH mode not because they make a conscious choice between pooled and private RH, but simply because they are not familiar with pooled RH. Of course, such important results are not simply esoteric econometric issues, but have important managerial

implications as they disentangle the relative effects of policy relevant variables on the overall familiarity and specific trip choice dimensions, which aids in the design and development of information/marketing campaigns customized to different population groups (as we discuss in Section 6.2). As indicated earlier, any action to enhance the propensity to pool rides for specific RH trips is contingent on first familiarizing the individual with the pooled RH service and getting the individual to the point of first use of the service.

The second outcome in our modeling system corresponds to the revealed preference (RP) choice of private versus pooled RH in the individual's most recent RH trip, conditional on being familiar with pooled RH (note that, by definition of pooled RH familiarity, a person who is unfamiliar with the pooled RH alternative will never be observed to choose the pooled RH alternative in the most recent RH trip). That is, the 594 individuals who are not "pooled RH-familiar" do not provide any information to aid in the modeling of choice between private and pooled RH choice in the RP context, other than helping in the estimation of the first (pooled RH familiarity) outcome and accounting for self-selection effects in the subsequent RP and SP choice outcomes. This second RP choice outcome is particularly useful in estimating the individual-level socio-demographic and built environment effects, though it does not contribute to the estimation of the trip-level attribute effects (because the trip-level attributes for the most recent RH trip are not available). Also, because of the rather few observations of individuals who clearly identified a trip purpose and chose pooled RH in their last RH trip (only 75 such individuals in total, with 18 doing so for commute, 10 doing so for shopping, and the rest for leisure), we are unable to further partition the RP choice of pooled versus private RH by trip purpose. Further, across all the RP RH trips, trip purpose was not clearly identified for 40% of cases. However, the SP choices (see below) allow us to estimate purpose-specific RH models. This is another unique aspect of our analysis; through appropriate combination of RP and SP choices, we are able not only to ground the choice to reality, but also obtain purpose-specific estimates for the trip-level attributes.

The last three outcomes are stated choices between private versus pooled RH, conditional on pooled RH familiarity, for (1) a commute trip, (2) a shopping trip, and (3) a leisure trip. The commute trip SP choice question related to travel to the work place (for a worker) or to school (for a student), and applied only to employed individuals or students (only 12 of the 359 individuals in our sample who indicated that they are familiar with pooled RH were both not a student and not employed; that is, the commute SP choice applied to 347 individuals). The other two purpose-specific SP choice questions applied to all 359 individuals with pooled RH familiarity.

The joint framework we adopt immediately accommodates multiple econometric issues associated with the joint RP-SP estimation. First, the presence of common individual-level stochastic latent constructs impacting the RP and SP choices leads to intra-individual correlation (which occurs since the same individual responds to the different choice outcomes) across all the RP and SP choices of the individual (as well as correlation of these RP/SP choices with pooled RH familiarity, as already discussed). Second, by allowing the coefficients on the stochastic latent constructs to vary across the RP choice and each of the SP choice purposes, we immediately allow for scale differences (that is, differences in the variance of utility due to unobserved factors)

between the RP choice and each of the SP choices (and also scale differences across purposes in the SP choice). Scale differences occur when choice responses are elicited in different environments (such as in the case of an observed RP setting versus a hypothetical SP setting), because the level of uncertainty in decision-making can vary based on contextual circumstances). Third, as discussed later in Section 6, once we have all the RP-SP results, we are immediately able to ground the estimates to the RP choice and obtain realistic purpose-specific estimates for all individual-level and trip-level parameters.

3.5. Data Collection

The sample used in the analysis is drawn from a 2019 multi-city Transformative Technologies in Transportation (T4) Survey. The T4 survey was conducted in Phoenix, Arizona, Atlanta, Georgia, Tampa, Florida, and Austin, Texas. In this paper, we use the sample collected from the Austin area. The survey distribution was undertaken using a purchased list of over 15,000 e-mails, as well as through social media advertisements and local area professional networks. A token financial incentive (a \$10 Amazon gift card) was offered for the first 250 responders, followed by a lottery drawing of other responders to win one of 100 additional \$10 Amazon gift cards. The distribution effort resulted in a convenience sample of 1,127 respondents. This sample was reduced to a final size of 953 respondents, after removing 174 individuals who did not respond to the ride-hailing section of the survey.

In addition to individual and household socio-demographics, home and work locations, and a battery of attitudinal/life-style perspectives, a section of the survey was focused on mobility-on-demand services, including familiarity, current use patterns, and a series of purpose-specific stated choice questions, all related to private and pooled RH. In Austin, pooled RH services (such as UberPOOL and LyftShare) have been available since 2014.

A comprehensive set of BE characteristics associated with an individual's residence is constructed, as discussed earlier. This process entailed the following four steps: (1) Geocoding residential location addresses provided by respondents, (2) mapping residential locations to census block groups, (3) extracting BE data from the U.S. EPA Smart Location Database (Ramsey and Bell, 2014), and (4) imputing missing values using MICE package in R with the classification and regression trees method (van Buuren and Groothuis-Oudshoorn, 2011).

The survey section on ride-hailing services first provides the definition of ride-hailing (defined as “mobility-on-demand services such as Uber and Lyft, which provide door-to-door transportation via a smartphone app”) and distinguishes between the two different forms of ride-hailing (“ride-hailing can be private, involving only you and your own travel companions, or shared [pooled], involving pick-up/drop-off of other people you don't know.”). This is followed by the question on pooled RH familiarity, as discussed in Section 3.4, which forms the basis for the first main outcome of pooled RH familiarity.

Information is then elicited on the choice of pooled versus private RH in the most recent RH trip (labeled the RP choice). The remaining three outcomes in our analysis pertain to the responses to three purpose-specific SP choice experiments. In each choice experiment, the

respondent is provided the option of choosing one of pooled or private RH (labeled the SP choice). All the RP and three SP choices in the analysis are conditional on pooled RH familiarity.

The SP experimental design is characterized by two trip attributes for each of the private and pooled RH modes: travel time (with the note that the travel time for pooled RH includes both “your waiting time and the extra time picking up/dropping off other passengers) and travel cost. A third trip attribute corresponding to the number of passengers in the pooling arrangement is included for the pooled RH alternative. The attributes and their respective levels are presented at the top of Figure 2 (each column of Figure 2 represents an attribute, and each row represents an attribute level (or a package of attribute levels that determine fare in the case of the fare structure attribute). The levels for the travel time and cost attributes for the private RH mode are defined with the objective of keeping the scenarios realistic. They are determined based on the average values of a publicly available RP dataset provided by a ride-hailing company, *RideAustin*. The average travel time of 13 minutes for private RH, as obtained from this data set, is used as a base SP time attribute level. The other attribute levels for time in the SP experimental design are obtained by varying this base attribute level by ± 5 minutes. Similarly, the average travel cost of \$15 for private RH, as obtained from the *RideAustin* data set, is set as a base SP cost attribute level, and varied by $\pm \$5$ to obtain other SP cost attribute levels. The corresponding time and cost values for the pooled RH mode are based off applying cost discount factors as well as a travel time increase percentage factor to the private RH values. In the absence of any publicly available dataset on pooled RH trip attributes, the discount factors and the additional travel time percentages are set in such a way that they are reasonable, account for the number of passengers in the pooled RH mode, as well as provide adequate variability in the attribute values between the private RH and pooled RH models (as well as adequate variability across scenarios). As one would expect, the pooled RH option always has a higher travel time and lower travel cost compared to the private RH option. Finally, the number of additional passengers is limited to what is reasonable within the carrying ability of a sedan, i.e. limited to three or fewer additional passengers.

In all, there are 243 (five attributes corresponding to the five columns in Figure 2 and three levels corresponding to the three rows of Figure 2 for a total of $3^5=243$) possible combinations between the attribute levels. From these combinations, 18 different scenarios are chosen using an orthogonal fractional factorial method, with the focus on isolating main effects. This experimental design is undertaken using the JMP (“John’s Macintosh Project”) software (JMP, 2020). Each individual is randomly assigned to respond to three scenarios, one scenario for each trip purpose.

3.6. Modeling Approach

The model employed in our analysis is a special case of Bhat’s (2015) Generalized Heterogeneous Data Model (GHDM) in which ordinal, nominal, and binary endogenous variables are considered simultaneously. In our case, all the endogenous (main) outcomes are binary. As explained earlier, unobserved stochastic psycho-social constructs serve as latent factors that provide a structure to the covariance dependence among the many endogenous variables, while the latent constructs themselves are explained by exogenous variables and may be correlated with one another in a

structural relationship. As illustrated in Figure 1, the SEM component defines stochastic latent variables as functions of exogenous variables and unobserved error components. In the MEM component, the endogenous variables (both the main outcomes as well as the indicators of the latent constructs) are described as functions of both the stochastic latent variables and exogenous 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. In our paper, we assume that these error terms are drawn from multivariate normal distributions (with the dimension equivalent to the number of latent variables). The latent constructs are created at the individual level (as a stochastic function of individual demographics and BE variables).

The resulting GHDM model is estimated using a maximum likelihood approach, using Bhat's (2018) matrix-based analytic approach to evaluate multivariate normal cumulative distribution (MVNCD) functions. To conserve on space, we do not provide the details of the estimation methodology, which is presented in an online supplement to this paper (see <https://www.caee.utexas.edu/prof/bhat/ABSTRACTS/PooledRH/OnlineSupp.pdf>).

4. SAMPLE DESCRIPTION

The final sample used in this paper includes 953 individuals. Table 1 presents descriptive statistics of the socio-demographic characteristics of these respondents. Compared to the Austin MSA population distribution statistics (U.S. Census Bureau, 2018), the sample has an overrepresentation of women (66.8% in the survey compared to 49.9% from the Census data), and is clearly skewed toward younger individuals (49.6% of adults 18 years or over in the age group of 18-29 years in our sample, relative to 23.7% of adults over the age of 18 years in this age group according to the Census). Non-Hispanic/non-Latino (NHNL) Whites are represented appropriately (50.8% relative to 51.6% from the Census). The Census and sample employment rates are difficult to compare, because many students who live in the Austin region (and who are also employed) may not provide their official residence as being in the Austin area for Census purposes. This may also be the reason why the sample shows a higher percentage (relative to the Census statistics) of individuals with a Bachelor's degree or higher (51.8% compared to 46.6% from the Census), a higher percentage living in a rented home (48.0% compared to 41.9% from the Census), and a higher percentage with a household income below \$50k (39.4% compared to 31.4% from the Census).

The sample skewness may be attributed to a number of factors, including the social media component of the recruitment campaign, the financial incentive scheme, and the survey topic. While any descriptive statistics on the endogenous variables from the current sample cannot be used to characterize the Austin area adult population because of this sample skewness, there is no reason to believe that the individual level causal relationships (how changes in exogenous demographics and psycho-social factors impact the endogenous variables of interest) estimated here would not be applicable to the larger population. Importantly, if the sampling strategy itself is not based on the endogenous variables (that is, the sample corresponds to the case of exogenous sampling, as is the case with our sampling approach), an unweighted estimation approach provides

consistent estimates, as well as yields more efficient estimates relative to a weighted procedure (see Wooldridge, 1995 and Solon *et al.*, 2015 for an extensive discussion of this point). Thus, in our model estimations, we use the unweighted approach.

Table 1 also presents the sample statistics for the residential BE variables that turned out to be important in our model (see bottom of the table). About 36.5% of respondents live in a highly urbanized neighborhood, with less than half of respondents living within 3/4th of a mile (about 15 minutes of walking time) to the nearest transit stop.

The sample distribution of attitudinal indicators for each of the three latent constructs is presented in Figure 3. The survey respondents are, in general tech-savvy (based on the level of agreement with the desire to be the first adopters of new technology and the need for ubiquitous internet connectivity, as well as the level of disagreement about technology being difficult to learn to use). The respondents, despite being young, educated, and tech-savvy, lie generally quite low on the sharing propensity scale, with a majority of individuals showing concern about sharing services or information. Despite this relative lack of enthusiasm for sharing, respondents seem enthusiastic about pursuing an environmentally friendly lifestyle. Particularly interesting is that a slight majority appears to favor raising gas taxes to reduce travel externalities, a “hot button” issue of debate in the U.S. today.

The descriptive statistics of the main outcome variables are provided in Table 2. In terms of pooled RH familiarity, just over a third of the sample is familiar with pooled RH. This also shows the high percentage of individuals who potentially can be pursued to increase RH familiarity, the first step in the move toward increasing pooled RH use. Of those familiar with pooled RH, a little more than a third used pooled ride-hailing in their last RH trip. This RP choice, in addition to providing valuable information to tease out individual-level effects, also serves as the ground reality for the choice of pooled RH. As can be observed from the SP choices, the percentage choosing pooled RH in the hypothetical scenarios is either about the same (for the commute purpose) or even higher (for the other two purposes) relative to the percentage choosing private RH. This is in stark contrast to the situation in the RP choice. Though this difference may simply be a result of the travel time and travel cost scenarios presented (which may be much more favorable to the pooled alternative than in reality, even though our experimental design strived to be as realistic as possible to current conditions), it is very likely that there is an overstatement of the use of pooled RH in the SP experiments. This underscores the potential pitfalls of using an SP-only choice approach, although the SP choice provides important trip-level insights related to the “time-cost-number of passengers” trade-offs. In our study, we are able to combine the realism from the RP choice with the rich trade-off insights from the SP choices.

5. MODEL ESTIMATION RESULTS

The final model specification was developed through a systematic process of analyzing alternate combinations of explanatory variables, while removing statistically insignificant ones. Continuous variables such as household income and trip times/costs were tested for effects using different functional forms, including a linear form, a nonlinear form based on piece-wise linearity, and

dummy variables for specific groupings. The sensitivity to cost and time was also interacted with individual-level variables, such as household income and the psycho-social variables (to reflect the decreasing sensitivity to cost with income). However, the final specification for cost/time turned out to be rather simple, including a simple linear form for these variables (though with different coefficients for different purposes).

For the non-continuous and non-nominal individual demographic and household characteristics, such as household income (captured in grouped categories) and household location (captured in the urban, suburban, and rural categories), dummy variables in the most disaggregate form were initially tested, and progressively combined based on statistical tests to yield parsimonious specifications.

Some variables that are not statistically significant at a 95% confidence level are still retained in our final specification due to their intuitive interpretations and policy implications. Also, these effects, even if not highly statistically significant, can inform specifications in future investigations with larger sample sizes.

In the next section, we discuss the results of the SEM model component of the GHDM, which relates the stochastic latent constructs to observed exogenous variables. This relationship is teased out during the full model estimation, where information on the indicators of the latent constructs, as well as the main outcomes themselves, are used to estimate the SEM coefficients. In doing so, we estimate the loadings of the latent constructs on the indicators, which constitutes one part of the MEM component. To keep the presentation focused, we do not present these loadings in the paper, but they are available in the online supplement to this paper. All of the latent construct loadings on the indicators had the expected signs.

5.1. Results for the Latent Constructs

The structural relationships between socio-demographic variables representing lifecycle stages and the latent constructs are presented in Table 3. Gender shows significant effects on tech-savviness and sharing propensity. The generally higher tech-savviness levels among men, though not found statistically significant in many earlier transportation studies (including Lavieri and Bhat, 2019a; Moore *et al.*, 2020; Nair and Bhat, 2020), has at least two possible explanations in the socio-technical literature. The first is that women tend to be more risk-averse than men (Borghans *et al.*, 2009) and the prospect of new technology can appear rather daunting to them. This result is also consistent with the literature on consumer behavior and human values. Specifically, the consumer behavior literature suggests that men are more likely to be drawn toward new experiences and stimulation (Tscheulin, 1994; Schwartz and Rubel, 2005; Vianello *et al.*, 2013). The human values literature suggests that there is a gender difference based on the notion of “risk as feelings”, according to which our instinctive and intuitive emotions dominate reasoned approaches when faced with risk (in our case, new technology can be viewed as a risk). Further, since women experience feelings of nervousness and fear more than men in anticipation of negative outcomes, the net result may be a heightened aversion to new technology (Croson and Gneezy, 2009; Loewenstein *et al.*, 2001). A second explanation is that women’s lower tech-

savviness levels may be explained by the still-existing gender roles and stereotypes, with women continuing to be viewed in society as the home-based multi-taskers responsible for being the “rock of the family” (with the almost exclusive role to stabilize day-to-day home affairs). This societal perspective can get translated into women’s lower levels of tech-savviness in multiple ways, including (a) women themselves internalizing societal views and being less receptive of technological novelty, (b) women not being provided as many upward mobility growth opportunities to contribute in high technology firms, and (c) women simply being time-poor because of familial responsibilities and not able to invest time in becoming aware of emerging technologies at the same rate as men are able to (see Bain and Rice, 2006; Bernardo *et al.*, 2015; Sudzina, 2015).

The gender effects on the second latent construct, sharing propensity, is also not surprising. While the human development literature indicates that women generally are more altruistic and sociable, the sharing propensity here refers to the specific issue of being in a relatively compact enclosed space with strangers. Personal safety and the risk of harassment in such close proximity are important concerns for women (Scott, 2003; Tirachini, 2020). Sarriera *et al.*, 2017 further observe that the fear of being paired with an unpleasant stranger and personal safety issues are primary reasons women avoid pooling (see also Scott, 2003). In addition to the service sharing element of the “sharing propensity” construct, another element of this construct is the information sharing element. Women tend to be more privacy-sensitive with online and personal information (Hoy and Milne, 2010; Rowan and Dehlinger, 2014). Thus, the positive male effect on sharing propensity is reasonable. Interestingly, in terms of gender effects on green lifestyle propensity, there is no difference between young men and women, while there is a clear lower GLP among older men relative to older women. This result suggests a narrowing gender gap in terms of green living in the younger generation, although the more prosocial values among women relative to men (and resulting environmentally conscious behaviors; see Gifford and Nilsson, 2014) is clearly evident in the older generation.

In relation to the effect of age on tech-savviness in Table 3, the results evidence the lower tech-savviness among the older group of respondents relative to their younger peers. This is perhaps one of the most well-established results in the socio-technical literature, with a multitude of explanations. These include the observation that younger individuals (especially the late millennials and the so-called Z generation) were born in a world of technology ubiquitousness and are “digital natives”, while older individuals find it more difficult to adapt to these new technologies (see Correa *et al.*, 2010; Helsper and Eynon, 2010). Older individuals also see less use of new technologies (Berkowsky *et al.*, 2018; Rogers *et al.*, 2017), and deliberately avoid new disruptive technologies to preserve current lifestyle habits (so as to maintain a self-perception of being in control of their lives and raise their mental self-esteem at a stage of life when their physical self-esteem may not be as high as during their yester years; see Marikyan *et al.*, 2019; Asmussen *et al.*, 2020).

The race/ethnicity effect in Table 3 reflects a lower propensity among NHNL Whites (relative to individuals of other race/ethnicities) to share space resources and disclose

personal/private information. While there may be several explanations for this result, perhaps the most critical factor is the “individualism-collectivism” cultural scale in shaping general shared values, norms, and behaviors of different cultural groups (Triandis, 2001). North and Western Europe and North America tend to be characterized by an individualistic focus and place high emphasis on the individual self and personal achievement, while people originating from collectivist cultural backgrounds (*i.e.*, Asian, South American, or African heritage) tend to consider themselves as part of a greater familial/cultural unit and operate as such to maximize community well-being rather than purely focus on individual achievement. The interdependence, solidarity, and priority of relationships within a collectivist culture stands in contrast to the values of autonomy, competition, and independence in an individualistic culture, in which “priority [is given] to their personal goals over the goals of their in-groups” (Triandis, 2001; Kahan *et al.*, 2007; Alba and Nee, 2003). Because Whites tend to originate from more “individualistic” backgrounds, it makes sense that they may be more possessive of space resources than individuals who come from a more collectivist cultural background.

The higher GLP propensity among those with high education is consistent with the earlier social-psychological literature (see, for example, Stern, 2000; Sundblad *et al.*, 2007; Franzen and Vogl, 2013). These earlier studies suggest that individuals with a higher education are (a) able to assimilate environmental information quickly, (b) more self-aware of the negative consequences of degrading the environment (such as the resulting health-related problems and global warming), (c) more cognizant of the actions that lead to degrading the environment (such as excessive driving) and benefiting the environment (such as using non-motorized means of travel), and (d) able to better project into the future and appreciate the trajectory of alarming environmental trends, even if these trends are very slow and do not pose an imminent danger to society. All of these factors result in individuals with a high education being generally more environmentally friendly.

The final two variables indicate that employed individuals tend to have a higher sharing propensity than their unemployed peers, and that individuals in high-income households are likely to be more tech-savvy and less green than individuals from relatively low-income households. The income-related tech-savvy effect is consistent with the notion that higher consumption power enables early access to new technologies and affords more opportunities for enhancing technology knowledge (Lavieri *et al.*, 2017; Liu and Yu, 2017). Also, higher income individuals, because of socio-cultural motivations for a luxury lifestyle (for example, signaling wealth, power and status, privileged access to limited resources, and/or uniqueness in the consumer space; see Chevalier and Gutsatz, 2012; Nwankwo *et al.*, 2014) are likely to be less green.

The three correlations corresponding to the three pairs of latent variables are shown at the bottom of Table 3. Tech-savviness is positively correlated (due to unobserved factors) with sharing propensity and GLP, and GLP and sharing propensity are also positively correlated. These are rather intuitive; individuals who are tech-savvy are intrinsically likely to be more open to efficient living conditions (thus increasing GLP; Seçken, 2005), and those intrinsically altruistic are likely to be high on both the GLP and sharing propensity spectrums.

5.2. Pooled RH Familiarity

The results for pooled RH familiarity are presented in the first numeric column of Table 4. Those with a high sharing propensity have a significantly higher familiarity with pooled RH, as expected. This is the single most important personality attribute impacting pooled RH familiarity; once sharing propensity is accounted for, there is no statistically significant remaining effects of tech-savviness and even GLP on pooled RH familiarity. Clearly, issues of personal safety, comfort being with strangers in close proximity, and information security are key considerations in pooled RH familiarity. Important also to note is that sharing propensity positively impacts the choice of the pooled RH mode in all the RP and SP choice experiments, engendering correlation between the familiarity and actual pooled RH choice.

In addition to the indirect socio-demographic influences through the sharing propensity latent construct, there are direct demographic and BE effects on pooled RH familiarity. Table 4 indicates that younger individuals are more likely than their older counterparts to be familiar with pooled RH, perhaps because pooled RH is perceived as a convenient and relatively inexpensive means to pursue trips with friends for late evening social occasions (see Kooti *et al.*, 2017).

The results also show that NHNL Whites are less familiar with pooled RH services, even after accounting for indirect ethnicity effects through the sharing propensity construct. In addition to general sharing propensity effects, white racial and structural privilege might be an additional factor that explains this result. The concept of identity-protective cognition suggests that “individuals selectively credit and dismiss asserted dangers in a manner supportive of their cultural identities” (Kahan *et al.*, 2007). This identity self-defense effect is particularly pronounced in Whites, who may be less likely to challenge systems that have benefitted them as they may perceive that challenging such systems may undermine the legitimacy of their hard work and current social/economic position (Kahan *et al.*, 2007). This may lead to a greater tendency and incentive for Whites overall to hold less egalitarian attitudes compared to other groups. Prior studies have examined discrimination in the context of ridesharing, and found that Whites who lived in majority homogenous white counties were “more likely to hold discriminatory attitudes with regard to race”, and thus may perhaps be less inclined or comfortable to rideshare, especially if there is a chance that they may end up sharing or pooling a ride with a person of color (Moody *et al.*, 2019).

Table 4 also shows that higher education increases familiarity with pooled ride-hailing, potentially because of better information exchange about emerging mobility services through extensive knowledge and social networks. In terms of household level variables, those residing in rented homes and those with high household income have higher pooled RH familiarity. The latter result is perhaps an indicator of more extensive knowledge networks (a similar result was obtained in Lavieri and Bhat, 2019a,b). In terms of BE effects, individuals living in more urbanized locations and that have good transit access are more likely than their counterparts in less urbanized locations and without good transit access to be familiar with pooled ride-hailing. This is not surprising, because pooling becomes easier to form in highly dense areas, and can provide an important supplement to traditional public transportation services (see Li *et al.*, 2019 and

Goodspeed *et al.*, 2019). Interestingly, while we explored multiple BE variables, density and transit access turned out to be the only significant variables for pooled RH familiarity, while population density appeared to provide a better fit in the revealed choice context, as discussed next.

5.3. RP Choice: Private Versus Pooled RH Mode

The results of the RP choice (conditional on pooled RH familiarity) are provided in the second column of Table 4 (note that these estimates account for self-selection, as discussed earlier). The latent variable effects have the expected direction for sharing propensity and GLP, with higher levels of these latent constructs corresponding to the higher probability of choosing pooled RH in the most recent ride-hailing trip. The effect of tech-savviness suggests a lower propensity to use pooled ride-hailing relative to private ride-hailing. Supporting this result, Lavieri and Bhat (2019a) observe that tech-savvy individuals are more likely to use private ride-hailing than the general population, but much less likely to use pooled ride-hailing relative to private ride-hailing.

In addition to the indirect socio-demographic influences through the latent variable effects, there are two direct socio-demographic effects and a BE effect on pooled RH choice in the RP scenario. Both the lower probability of NHNL White individuals to choose pooled RH, and the higher probability of educated individuals to choose pooled RH, reinforce the effects of these variables on pooled RH familiarity. The same is the case with the BE effect corresponding to high population density (as discussed earlier, the designation of urban/suburban/rural is also based partly on population density, but includes an employment density component; the results for pooled RH familiarity and the RP choice suggest that, while employment density may be important for pooled RH familiarity, the driving factor for actual pooled RH choice is population density).

5.4. SP Choices: Private Versus Pooled RH Mode

The SP choice results are presented in the final three columns of Table 4. As expected, because the SP experiments include only the trip-level attributes, the SP results do not provide much information to estimate individual-level estimates beyond that already embedded through the individual-level latent constructs. In fact, after including the latent construct-mediated effects of individual socio-economics and demographics, we did not find any remnant and statistically significant direct effects of these individual-level variables in the SP choice model components.

Our approach enables the incorporation of observed and unobserved individual heterogeneity in time/cost sensitivities by using the stochastic latent constructs as moderators of the trip attributes in the choice utilities. Then, the explanatory variables of the stochastic latent construct, along with the error term embedded in the stochastic latent construct, immediately capture sensitivity variations across individuals. However, in our empirical context, after capturing the main effects of the time and cost variables, there was little to no magnitude shifts in the effects of interaction variables, including sharing propensity with number of passengers (to investigate if those low on sharing propensity are particularly unwilling to pool as the number of passengers in the pooled arrangement increases), sharing propensity with travel time (to examine if the presence of strangers increases the disutility of time traveling), and additional passengers with travel time

(to test if individuals are willing to tolerate additional passengers more for short trips but not long trips). The absence of such interaction effects in our study suggests that individuals have a fixed dis-utility to pooling RH rides depending upon their psycho-social characteristics, the number of passengers, and travel time/costs, with no interactions between these elements. On the positive side, this suggests that once we are able to get individuals to accept and use pooled RH, it could potentially open up a number of possibilities to increase vehicle occupancy regardless of trip time.

Additionally, a very interesting observation in our SP choice model component is that the coefficients on the latent constructs for the SP leisure choice experiment were almost exactly identical to those from the RP choice model component. In fact, the coefficient on the tech-savviness variable was identical to three decimal places, and all other latent construct effects in the RP and SP leisure model components were not statistically significantly different at any reasonable level of significance. Thus, we “pinned” the latent construct coefficients for leisure to that from the RP choice (that is, constrained the coefficients on the latent constructs for the SP leisure and RP choices to be equal in our joint estimation). The net result, in our framework, is that the scale of the overall RP error is identical to that of the overall SP leisure choice error (because the overall error includes the normalized standard error as in any binary choice model plus the linear combination of the errors in the individual latent constructs multiplied by the corresponding coefficients on the latent constructs). It also so happens that the majority (65%) of the RP RH trips (for which a clear purpose was identified) are for leisure activities, so this result is reasonable. That is, individuals responding to the SP leisure experiment may have perceived it as being pretty similar to their most recent RH trip, except with different travel times and costs, and so the level of uncertainty embedded in the two choice processes are about the same. Of course, this does not mean that there is no bias in the SP experiment, as individuals may attempt to overstate their socialness and civic responsibility in the hypothetical scenarios. But, by pinning the SP leisure choice to the RP choice, we are able to develop an appropriate model for pooled versus private RH for all purposes at once, anchored to reality (the procedure is discussed in Section 5.7). The implied scales (square root of variance) based on our model estimates for the RP and SP total errors are 1.236 for the RP error, 1.046 for the SP commute error, 1.157 for the SP shopping error, and 1.236 for the SP leisure error. The scale for the pooled RH familiarity error term is 1.041.

Proceeding to the results for the individual-level latent construct effects in the SP choice scenarios, these effects are consistent with those from the RP choice. But the SP scenarios differentiate the effects by purpose, and indicate that tech-savvy individuals are particularly less likely to use pooled RH for the shopping and leisure trip purposes relative to the commute trip purpose (even after accounting for the higher scale value for the leisure purpose). On the other hand, those who are high on the sharing scale use pooled RH more for the commute/shopping purpose, but not as much for the leisure purpose. The effect of GLP is to increase pooling tendency more uniformly (after accounting for the scaling) across trip purposes.

5.5. Value of Travel Time (VTT) and Willingness to Share (WTS) Analysis

The expected values of VTT and WTS may be computed in a straightforward fashion from the trip-level attribute estimates in Table 4 (see toward the bottom of Table 4). Overall, the VTT estimate is \$27.80 per hour for commute travel, \$19.40 per hour for shopping travel, and \$10.70 per hour for social/leisure travel. The results show clear variation across the trip purposes, unlike the finding from Alonso-González *et al.* (2020a) of no variation between commute travel and leisure. Travel time holds a premium to get to work, possibly because of the need to be at work on time. The VTT estimate for commute is similar to that from Lavieri and Bhat (2019b), who examine pooling in the context of a shared AV system as opposed to our analysis here of pooling in the context of ride-hailing. The leisure purpose VTT in our analysis is about half that of Lavieri and Bhat, suggesting that, while individuals are willing to be patient in today's human-driven environment to travel with others for leisure, they will be less accommodative of pooling delays in an automated world. Both Alonso-González *et al.* and Lavieri and Bhat did not consider a separate shopping purpose, but our results indicate a VTT between commute and leisure for the shopping purpose. Also, the average estimate of \$19.30/hour across all the trip purposes is almost identical to that obtained by Alonso-González *et al.* The closeness in VTT across different geographical regions (Dallas-Fort Worth in Lavieri and Bhat, the Netherlands in Alonso-González *et al.*, and Austin in the current study) with respect to pooling is quite remarkable.

In terms of the willingness-to-pool estimates (we will use the term willingness-to-share or WTS in a pooled RH setting to avoid ambiguity with the more familiar willingness-to-pay or WTP acronym), the results indicate that individuals are willing to pay, on average, 62 cents not to have an additional passenger for commute travel. The corresponding values are \$1.70 for shopping travel and \$1.32 for leisure travel. Clearly, individuals are very sensitive to an additional passenger for shopping, and the least for the commute. This heightened sensitivity toward additional passengers for shopping is to be expected, given the convenience in timing and carrying groceries/consumer products afforded when there are fewer passengers. As already discussed, this willingness to pay to avoid traveling with strangers represents a fixed cost, and is independent of travel time, reinforcing the results from Lavieri and Bhat on this front.

Further insights about the trade-off between time and additional passengers may be derived from the WTS and VTT estimates for each trip purpose. In particular, for commute travel, reducing one passenger in a commute trip has the same monetary value as reducing the travel time by 1.35 minutes. The corresponding values for a shopping trip and for a leisure trip are 3.7 minutes and 2.9 minutes, respectively. Once again, this is a fixed time cost of an additional passenger, regardless of travel time. Overall, these values are much lower when compared to actual delays caused by an additional passenger in a ride.

5.6. Goodness of Fit

The goodness of fit of the GHDM model may be compared against an independent binary probit (IBP) model that ignores the jointness among the different binary outcome variables caused through the latent stochastic constructs. The GHDM model and the IBP model are not nested, as

the latter model does not provide a mechanism to incorporate the latent constructs. Therefore, for a fair comparison between the GHDM and IBP models, we compute the average probability of correct prediction and the likelihoods for only the five main outcome variables of RH familiarity, RP choice, and the three SP choices. Also, to recognize the effects of socio-demographic and BE variables to the fullest extent possible in the IBP model, the full set of these variables are included as explanatory variables.⁴ Table 5 provides multiple disaggregate measures of fit for the GHDM model and the IBP model.

The GHDM model outperforms the IBP model with respect to the average probability of correct prediction of the joint combination of the main outcomes. These average probabilities may appear low, but considering that the five outcome variables can produce a total of $2^5 = 32$ outcome combinations, the value of 0.086 for the GHDM model is close to 3 times the probability of correct prediction due to random chance (0.03125). The predictive log-likelihood at convergence of the GHDM is also quite a bit higher than for the IBP, though the models cannot be compared using a nested likelihood ratio test. But we can use the familiar non-nested likelihood ratio test to informally compare the two models, because the indicator variables used in the measurement equation of the GHDM are included solely for the purpose of model identification and do not serve any purpose in predicting the endogenous choice bundle of interest once the model is estimated. To do so, we evaluate a predictive log-likelihood value $L(\hat{\theta})$ for each of the two models at the model convergent values focusing only on the primary outcomes of interest. Then, one can compute an informal predictive adjusted likelihood ratio index (PALRI) of each model with respect to the log-likelihood with only the constants as follows:

$$\bar{\rho}^2 = 1 - \frac{L(\hat{\theta}) - M}{L(c)}, \quad (1)$$

where $L(\hat{\theta})$ and $L(c)$ are the predictive log-likelihood functions at convergence and at constants, respectively, and M is the number of parameters (not including the constant(s) for each dimension and not including the ordinal indicators) estimated in the model (see Ben-Akiva and Lerman, 1985, page 172).⁵ If the difference in the indices of the two models is $(\bar{\rho}_2^2 - \bar{\rho}_1^2) = \tau$, then the probability

⁴ The reader will note that the GHDM model effectively includes 17 dependent outcomes, corresponding to the five main outcomes of interest (those provided in Table 5) as well as the twelve indicator variables (to which the latent psychological constructs are loaded onto). However, the twelve indicator variables solely provide information to estimate the structural equation model (SEM) component of the GHDM model, and do not really add to the predictive power of the five main outcomes other than through their use to identify the latent constructs. In contrast, the IBP model has only five dependent outcomes, corresponding to the five main outcomes. Thus, any comparison of the GHDM and the IBP needs to be undertaken on the basis of predictive ability for the five main outcomes.

⁵ We refer to our implementation of the PALRI as being informal because the test is strictly applicable only in the case when the $L(\hat{\theta})$ refers to the convergent log-likelihood when the parameters are being directly estimated. In our case, the $L(\hat{\theta})$ for the GHDM model is not based on a convergent log-likelihood value, but based on a post-processed predictive log-likelihood value where the estimated model parameters θ are applied in a subsequent step to obtain the probability of choice for the five outcomes leading up to the constructed $L(\hat{\theta})$ value.

that this difference could have occurred by chance is no larger than $\Phi\{-[-2\tau L(c) + (M_2 - M_1)]^{0.5}\}$ in the asymptotic limit. A small value for the probability of chance occurrence suggests that the difference is statistically significant and that the model with the higher value for the adjusted likelihood ratio index is to be preferred. The PALRI values are provided in the last row of Table 5. The non-nested adjusted likelihood ratio test (in its informal version used here) returns a value of Φ (-7.827), which is literally zero, reinforcing the superior $L(\hat{\theta})$ from the GHDM model compared to the IBP model.

5.7. Integrating RP and SP Choice Estimations

The joint RP-SP choice and pooled RH familiarity need to be translated in a way that one can expect “true” predictions anchored to the RP choices. The RP choice does not distinguish pooled RH tendency by trip purpose, nor does it provide the effects of trip-level attributes. But it does help estimate the individual-level construct effects as well as the effects of exogenous variable (socio-demographic and BE) effects. The SP choices provide trip purpose-specific estimates, as well as enable the estimation of the effects of trip-level attributes. Both the RP and SP choices aid in estimating the latent construct effects.

The main issue in integrating the RP and SP choices is to obtain appropriate “RP” constants for each of the three trip purposes, because the SP constants are likely to be biased. To do so, the first step is to anchor one of the SP choices to the RP choice, which has been discussed earlier. Based on the effects of the latent constructs, the overall implied scale, and the fact that most of the RP choice instances relate to the leisure purpose, we tie the SP social leisure purpose closely to the RP choice. In a second step, we replicate the SP trip-level attributes in the RP choice scenario. In a third step, we replicate the individual-level socio-demographic and BE variables appearing in the RP model component (that is, the race, education, and population density variables) in each of the three SP scenarios. In a fourth step, we constrain the trip-level coefficients in the RP choice component to be equal to those estimated from the SP leisure choice component, and set the exogenous variable coefficients for the SP leisure choice component to be equal to those from the RP choice estimation. In the fifth step, we constrain the exogenous variable coefficients in the SP commute and SP shopping choice model to be equal to the scale-adjusted coefficients from the RP choice estimation (that is for example, we inflate the high education coefficient of 0.592 from the RP model by the value of (1.236/1.046) for the SP commute to bring the coefficient up to the scale of the RP choice error). In a sixth step, we inflate the trip-level and the latent variable effects for the SP commute and SP shopping purposes similarly to the scale adjustment in the fifth step. With all of these, we now have all the scales matched up to the RP scale. In the seventh step, we re-estimate the joint five-variate binary probit model (including the pooled RH familiarity dimension) with all the constraints above (and also constraining all the coefficients for the RH familiarity component as originally estimated), but estimating (only) the constants for the four (RP and SP) choice dimensions, with the scale for all four choice dimensions set to the RP scale of 1.236 (and the scale for the RH familiarity set as originally to 1.041, and the correlation matrix retained from the original estimation). Let these constants be RPC, SP Commute (SPC), SP Shopping (SPS), and

SP Social/Leisure (SPSL). In the eighth step, we obtain the “RP” leisure constant as being equal to RPC, the “RP” commute constant as $RPC+SPC-SPSL$, and the “RP” shopping constant as $RPC+SPS-SPSL$. Finally, we discard the RP choice entirely, and retain all the estimates from the remaining four dimensions (including deleting the row/column corresponding to the RP choice from the correlation matrix). The estimates now on all the variables are appropriately scaled, and the estimates now correspond to the “RP” choice of pooled RH familiarity, and the purpose-specific “RP” choice coefficients. The scale for “RH familiarity” is 1.041, and the scales for all the other three “RP” choice components are 1.236. The final result of this process is shown in Table 6, and is used in the subsequent ATE analysis. Importantly, unlike in the case of the SP estimation results from Table 4 where the pooled RH constant turned out to be positive (because of the substantial bias in the SP choice toward pooled RH), the RP-anchored purpose-specific models in Table 6 reveal a negative sign on the constant. Based on Table 6, the predictions for each of the three trip purposes are as follows: 21.8% pooled RH for the commute purpose, 44.6% pooled RH for the shopping purpose, and 34.9% pooled RH for the leisure purpose. The pooled RH percentages are clearly lower than the pooled RH percentages implied by the SP choices (48% for commute, 67% for shopping, and 62% for leisure), corroborating our earlier suspicion of an overstatement bias effect in the SP responses.

6. POLICY IMPLICATIONS

6.1. Background and Preparation

The results in the previous section are helpful in obtaining a sense of the direction of the effects of variables, but are not too insightful in terms of magnitude effects. But policy actions would benefit most from actions that are likely to be quite effective in achieving a specified goal. In the context of the current paper, this specified goal would be to increase the share of people selecting the pooled RH mode rather than using the private RH mode, conditional on choosing to ride-hail (the current paper does not focus on the broader choice to ride-hail, which has been the focus of many other studies in the past, as discussed in Section 2). From a notation standpoint, for each trip purpose X , the goal would be to increase the joint bivariate probability $\text{Prob}(\text{Pooled RH Familiarity} = 1, \text{Pooled RH for Trip Purpose } X = 1)$. This bivariate probability is computed by marginalizing over the four-variate probability (of pooled RH familiarity and use of pooled ride-hailing for each purpose) from Table 6.

An additional challenge with the estimation results in the previous section is that they do not provide the relative magnitudes of the direct effects of exogenous variables and the indirect effects through the psycho-social constructs. This is important to develop effective policies aimed at specific demographic groups. For example, should campaigns directed toward older individuals be focused on raising familiarity levels of pooled RH or their environmental consciousness levels? Should funds to increase pooled RH among NHNL Whites be channeled toward promoting sharing as a generic concept in life or raising pooled RH awareness? Are there specific trip purposes that are particularly suited to position pooled RH strategies? How much effect might such policies have

relative to changes in trip-level attributes, such as reducing delays in picking up/dropping off additional passengers or providing larger cash reductions for pooled RH use?

These and other questions related to increasing pooled RH use would need both an assessment of the total effect of an exogenous variable on the bivariate probability of pooled RH familiarity and purpose-specific pooled RH use, as well as a breakdown of this total effect into each of six sub-effects: RH familiarity direct effect, RH familiarity effect through sharing propensity promotion (because sharing propensity is the only latent construct affecting pooled RH familiarity), tech-savviness enhancement effect, sharing propensity promotion effect, green living encouragement effect, and the remaining pooled RH use direct effect. This partitioning can be done using the Average Treatment Effect (or ATE effect; see Angrist and Imbens, 1991, and Heckman and Vytlačil, 2000), which is a metric that computes the impact on a downstream posterior variable of interest due to a treatment that changes the state of an antecedent variable from A to B. For example, if the intent is to estimate the treatment effect of densifying land-use on RH pooling use for the commute, A can be the state where the individual is in a rural area, and B can be the state where the individual is in an urban/suburban area. The impact of this change in state is measured in terms of the change in the shares of the bivariate probability of interest between the case where all individuals in the dataset are in state A and the case where all the individuals in the dataset are in state B. If a variable impacts RH familiarity or RH pooling use for the commute through a mediating latent variable (such as sociodemographic effects through the tech-savviness construct), one can use the estimates from Table 6 and Table 7 to partition out the ATE by its sub-effects.

In addition to the indirect and direct effects of the individual-level characteristics, we also compute the direct ATE effect for the trip-level variables. For travel time, the base case corresponds to the private RH travel time and pooled RH time as in the presented choice experiments. The average time across all individuals and trip purposes is 15.1 minutes for private RH and 22.8 minutes for pooled RH, with the average difference being 7.7 minutes (these values did not vary too much by trip purpose). In the treatment case, we reduce the pooled RH travel time by 5 minutes, resulting in an average travel time difference between the pooled and private RH of 2.7 minutes (this is about the difference per passenger that simulation studies suggest can be obtained between pooled and private RH rides; see Alonso-Mora *et al.*, 2017). For travel costs, we again retain the presented costs in the SP experiments for the base case, and then decrease the pooled RH costs by \$1.00 in the treatment case. The average cost across all individuals and purposes is \$13.20 for private RH and \$9.60 for pooled RH in the base case, with the average difference being \$3.60. In the treatment case the cost difference between the two alternatives increases to \$4.60. Finally, for the “number of passengers” attribute, we again retain the SP experiment values for the base case (average of 2.0 passengers across purposes and individuals). For the treatment, we increase the number of passengers by one.

To compute the relative magnitudes of the contribution of each sub-effect, we ignore the directionality of the ATE effect and compute percentages as a function of the sum of the absolute values of each sub-effect. These percentages are provided as the relative contributions of each sub-

effect (specific to each trip purpose). To conserve on space, and also because almost all of the variable effects had similar effects on the three trip purposes (with differences in absolute magnitude of effects, but similar relative magnitude of each of the sub-effects), we present only the results for the commute purpose in this paper in Table 7 (the corresponding results for the shopping and leisure purposes are available in the supplement to this paper). However, as appropriate, we will comment on the magnitudes of effects of all purposes in our discussion. For completeness, we also provide the overall ATE of each variable, which would be the sum of the individual sub-effects (after considering the directionality of effect).

The overall ATE values are presented in the last column of Table 7, and are to be interpreted as follows. Consider the ATE effect of age. The last column shows a value of -0.144. This implies that if 100 younger individuals (18-24 years of age) were replaced by 100 older individuals, about 14 fewer individuals (of the 100) would use pooled RH. Yet another way to view this would be that, given the percentage share of pooled RH for the commute is 21.8 from the base case (corresponding to the predicted shares from Table 6), the pooled RH share decreases from 21.8% to 7.4% because of the age “treatment”. Other ATE values may similarly be interpreted. The “% contribution by mediation through...” columns are to be interpreted as follows. The value of -77 in the column for “RH familiarity direct effect” for the age variable (change from 18-24 years to the 55+ age category) indicates that, in terms of magnitude, 77% of the sum of the contributions of each sub-effect (ignoring directionality) to the ATE change in pooled RH use is due to an RH familiarity direct sub-effect. This has a negative sign, indicating that the age “treatment” leads to a reduction in pooled RH familiarity. The reader will note that the sub-effect categories are labeled in a way that a positive change in the sub-effect would generally lead to a positive increase in pooled RH shares. Thus, the sub-effects are labeled as “RH familiarity direct effect”, “RH familiarity sharing propensity increase”, “tech-savviness decrease”, “sharing propensity increase”, “GLP increase”, and “tech-savviness increase”. For example, older adults are generally less tech-savvy than younger adults, which leads to a positive “tech-savviness decrease” sub-effect (see the entry “20” in this column for the age effect), which then has the result of increasing pooled RH because higher tech-savviness has a negative effect on pooled RH (in favor of private RH).

6.2. ATE Discussion

The ATE effect of gender is presented first in Table 7. The overall ATE effect (last column) indicates that men are slightly more likely to use pooled RH relative to women (this holds also for shopping, but there is literally no overall effect of gender for the leisure purpose). When partitioned into the component effects, we observe that part of this overall ATE effect is because men are more tech-savvy, and tech-savviness tends to strongly favor private RH rather than pooled RH (hence the negative sign in the “tech-savviness decrease” column). But men also are more likely than women to use pooled RH because of a higher sharing propensity, fueled by less concerns about personal safety and security. Thus, even though the net difference between men and women is tempered because of these opposing effects, our analysis provides insights regarding how best

to position information campaigns and pooled RH services toward men and women. One possibility to promote pooled RH among men is to appeal to their civic sense of responsibility and concern for the environment. As indicated earlier, except in the group of older adults (over 55 years), we did not discern any difference in green lifestyle propensity (GLP) between younger men and younger women. Further, there is a relatively high and strong unobserved correlation between tech-savviness and GLP. Thus, young men may be persuaded by emphasizing the benefits in terms of lesser general mobile-source emissions (due to lower VMT through pooling) as well as a decrease in traffic delay-caused emissions (due to lower congestion levels through pooling). More generally, the eco-friendly and low carbon footprint afforded by pooled ride-hailing can be emphasized. On the other hand, for women, the focus should be on efforts directed toward personal safety and information security, in addition to promoting “greenness”. An issue that does seem to cause consternation among women is being assaulted/harassed by a fellow passenger, which has led to women-friendly RH platforms (such as Safr in the U.S.) that offer sensitivity training to drivers, have more women drivers, have zero tolerance policies of passengers for any infractions, and include an SOS button accessible to each passenger. Social-network-based pooled RH schemes can also be an interesting solution to privacy and security concerns in pooled rides (see Richardson *et al.*, 2016; Wang *et al.*, 2017). In addition to these RH service provision enhancements, information campaigns that actually emphasize the benefits of being in a setting with more than one individual in the vehicle may also be beneficial. In fact, in a study by Sarriera *et al.* (2017), a reasonable fraction of women indicated that they used pooled RH because of feeling more secure with a person in addition to the driver. Finally, in the context of gender, the overall ATE effect for shopping is higher in magnitude than for the commute (and remains negative); that is, women are particularly unlikely to use pooled ride-hailing for shopping trips. This may be attributed to the fact that women are more responsible for personal, family, and shopping errands in the family, and so tend to chain multiple activities in the same sojourn from home (see McGuckin and Nakamoto, 2004). Such chaining involves carrying and storing food and other perishable goods during the trip, and pooled ride-hailing is very inconvenient for this purpose. Thus, it seems more effective to position pooled RH strategies directed at women for the commute trip purpose.

Age has a much stronger overall effect relative to gender. Our results indicate that, while older adults are less likely to use pooled RH because of being less familiar with pooled RH service as well as being less green, younger adults are actually less likely to use pooled RH based on their higher tech-savviness levels. Overall, the former effect more than compensates for the latter effect, leading to a lower RH pooling propensity among older adults (this is again another instance where simply examining the overall ATE effect provides limited insights, relative to the rich insights obtained in the current study through our ATE partitioning approach). The incorporation of pooled RH familiarity is a particularly salient feature of our model. The socio-technical and related literature (see Piao, 2016; Nair and Bhat, 2020) points to the combination of a lack of knowledge networks as well as enthusiasm as being the primary reasons that an individual may not be familiar with a specific technology. Our sub-effect results indicate that efforts to raise pooled RH

familiarity levels among older adults would be much more effective than attempting to raise environmental consciousness levels. This can perhaps be achieved by enhancing enthusiasm among older adults through invoking the advantages of a pooled arrangement as a means to open up new socialization possibilities. This might particularly appeal to the very elderly who have diminished physical accessibility and face potential social exclusion otherwise. Promoting pooled use as a way to avoid the “hassle” of finding parking spots close to destination points, and providing specialized pooled RH services for older adults, can be other effective ways to instill a sense of mobility control in this older adult group (see Asmussen *et al.*, 2020). Also, as for men, the higher tech-savviness levels among younger adults and the resulting association with GLP can be gainfully harnessed to promote pooled RH in this group through customized eco-friendly campaigns. Overall, it is promising that younger adults (especially the late millennials and the Z generation) are more likely to use pooled RH, especially because such individuals are now the majority of the labor force in the U.S. (Pew Research Center, 2018). This effect is particularly strong for the shopping trip purpose, based on the overall ATE effects (-0.213 for shopping compared to -0.144 for the commute purpose).

NHNL Whites have an overall lower propensity to use pooled RH, with reinforcing component effects. That is, this overall lower propensity is because NHNL Whites are not as familiar as their peers about pooled RH, have a lower sharing propensity, as well as through a strong direct negative effect on pooling. These reinforcing findings underscore the need to examine social justice and equity in transportation provision more generally (the overall ATE effect magnitude and the percentage contribution of the sub-effects are about the same across trip purposes). Of course, there is a strong contribution in this race/ethnicity effect attributable to the direct effect, separate from a RH familiarity and sharing propensity effect, suggesting the need for much more research into the “why” of this reluctance among NHNL Whites to pool. As indicated earlier, one possibility would be simply the issue of anxiety among Whites in being with other individuals, given the historical “exclusiveness” the white race has been used to. Studies examining ways to identify how individuals may be steered toward being less sensitive to the presence of strangers in a ride-hailing trip would certainly be valuable. For instance, some studies in the prejudice literature (see for example, Zebrowitz *et al.*, 2008; Barlow *et al.*, 2012) suggest that creating opportunities for first positive social experiences with strangers may help in breaking the anxiety barrier. This may be achieved by promoting the use of pooled services through a limited-time cost subsidy program (or even a limited number of free pooled RH rides), which can then potentially lead to a snow-balling effect on the use of future pooled ride-sharing.

The magnitude of the education level is second to that of the age effect in influencing pooled RH choice. The component effects through pooled RH familiarity, green lifestyle propensity, and the direct effect are all positive and reinforcing. Significant fractions of the education effect are through the pooled RH familiarity effect and a direct effect (the overall ATE magnitudes are similar across trip purposes, but the relative magnitude of the direct effect drops from 50% for the commute to 36% for shopping and 39% for leisure; the GLP sub-effect is much lower and ranges from 3% for the commute purpose to 6% for leisure). Additional investigations

to better understand this direct effect would be beneficial. In the meantime, expanding the knowledge network groups of those less educated through direct messaging efforts to make them better aware of pooled RH services can increase the uptake of the pooled RH mode.

Employment status, renting residence, and household income all have an overall positive impact on pooled RH choice, though the magnitude of the “renting residence” effect is much higher. The magnitudes of the effects (and sub-effects) of these three variables are similar across trip purposes, with the exception that the overall income effect is almost non-existent for the leisure purpose. While employment operates exclusively through a sharing propensity increase effect (though split between the impact of an increased sharing propensity on pooled RH familiarity and on pooled RH choice), and household tenure represents a direct effect, household income operates through multiple effects, including a familiarity sub-effect, a tech-savviness sub-effect, as well as a green lifestyle sub-effect.

The BE effects are all consistent with the notion that pooled RH is likely to have a higher demand in urban, high transit access, and high population density areas. These areas also tend to be the highly congested pockets of a city. The implication is that city public agencies can perhaps work closely with TNCs to provide deep subsidies for pooled rides tied to the resulting reduction in overall externality costs. An additional factor that should make this appealing to TNCs is that, from an operational perspective, urban (dense) areas are the most suitable environment for the efficient operation of pooled ridesharing (because the demand is concentrated and thus matching becomes easier). Of course, there needs to be a careful balancing here, lest pooled RH starts drawing away from active travel modes (walking and bicycling) and transit modes in these dense areas. If a higher share of current active mode and transit travelers shift to pooled RH (rather than those currently using solo-auto modes or even private ride-hailing), the result would be added traffic, not less. To discourage the substitution of very short-distance “walkable” trips by ride-hailing, a pricing scheme that more heavily prices the first mile, except if the patron is mobility-challenged or is using RH pooling strictly to access a fixed route transit system (see later, though how this can be enforced can get tricky), would be helpful. To avoid cross-substitution effects between pooled RH and transit, it is critical that cities consider an integrated (both in terms of service as well as payment) pooled RH and transit service. Essentially, pooled RH could serve as a mini demand-responsive transit (DRT) service that feeds into fixed route transit systems for first-mile and last-mile connectivity. The combination of the resulting transit ridership increases and the subsidies to recognize the decrease in externality costs can allow such an integrated pooled RH-transit service to be very competitively priced. Of course, a politically less palatable alternative that may also help drive pooled RH demand would be to impose an additional tax burden for single occupant auto trips and private RH in central areas of a city.

The ATE results related to the trip-level attributes are listed toward the bottom of Table 7, and constitute direct effects on pooled RH choice. Travel times and travel costs generally are more important than the number of passengers in the pooled RH mode for the commute purpose, but individuals become increasingly sensitive to the number of passengers for shopping and leisure trips (in fact, the ATEs for an additional passenger are higher than the ATEs for time and cost for

these two non-commute purposes; also, while there is some variation in the time, cost, and number of passengers ATEs across the shopping and leisure purposes, these ATEs are very similar in magnitude). In the context of the commute, the ATE effect for time suggests that a decrease of five minutes for pooled RH (a change, on average, from a 7.7 minutes differential between the pooled and private RH to 2.7 minutes) is estimated to lead to an additional four individuals (out of 100) taking up the pooled RH mode, while a decrease of \$1.00 in pooled RH services (a change, on average from a \$3.60 differential between the private and pooled modes to \$4.60) is estimated to result in an additional two individuals (out of 100) taking up pooled RH. The result of an increase by one additional passenger, on the other hand, leads only to about one less individual taking up the pooled RH mode.⁶ Again, individuals are the most sensitive to travel time for commute trips relative to the other two purposes, while also the least sensitive to the number of additional passengers for the commute purpose. Given the particularly low uptake of pooled RH for commute trips (relative to other trip purposes), there is scope for promoting dynamic pooled RH for commute trips, but only as long as the service is operated efficiently with minimal detour and pick-up/drop-off delays. Of course, this result may need to be put on hold for a couple of years now until the full impact of the current COVID pandemic gets behind us.

7. CONCLUSIONS

In this paper, we develop a comprehensive model for the choice between pooled versus private ride-hailing. The primary source of data for the analysis is drawn from a 2019 multi-city Transformative Technologies in Transportation (T4) Survey, based on responses from 953 respondents from the Austin, Texas area. This survey data is supplemented with a procedure that geocoded residential location addresses of respondents and mapped the locations to built environment attributes obtained from the U.S. EPA Smart Location Database (SLD). Bhat's (2015) Generalized Heterogeneous Data Model (GHDM) is used for modeling purposes.

Our results underscore the value of using psycho-social latent constructs in the adoption of current and emerging mobility services, both in terms of the improved prediction fit as well as in terms of proactive strategies to promoting the adoption of pooled RH services. Three psycho-social constructs turned out to be important in our analysis: tech-savviness, sharing propensity, and green lifestyle propensity (GLP). While higher levels of tech-savviness are associated with lower pooled RH use (that is, higher private RH use), those with a higher sharing propensity and GLP are more likely to the pooled RH mode. Further, by partitioning overall demographic effects on pooled RH choice into a pooled RH familiarity sub-effect, a direct sub-effect, as well as sub-effects through the psycho-social constructs, we are able to extract rich insights into positioning and targeting strategies for pooled RH promotion in ways that are simply unobtainable through a simple direct effects analysis. For example, our sub-effect results indicate that efforts to raise pooled RH familiarity levels among older adults would be much more effective than attempting to raise

⁶ Important to note also is that our ATE values are consistent with the VTT and WTS values estimated earlier. From Table 7, the VTT for commute may be estimated as $(0.039 \times 60/5)/0.017 = \27.5 per hour, and the WTS for commute may be estimated as $(0.011/0.017) = \$0.65$ or 65 cents.

environmental consciousness levels in this group. Similarly, our results suggest that NHNL Whites have an overall lower propensity to use pooled RH, because individuals belonging to this race/ethnicity group typically are not as familiar as their peers about pooled RH, have a lower sharing propensity, as well as evidence a strong direct dislike for pooling. These reinforcing sub-effects underscore the need to examine social justice and equity in transportation provision, and ways to identify how individuals may be steered toward being less sensitive to the presence of strangers in a ride-hailing trip.

Our results also provide estimates regarding the value of travel time (VTT) and willingness to pool with strangers (WTS), specific to each of the three trip purposes. Overall, the VTT estimate is \$27.80 per hour for commute travel, \$19.40 per hour for shopping travel, and \$10.70 per hour for leisure travel. The results show clear variation across the trip purposes, unlike the finding from Alonso-González *et al.* (2020a). In terms of WTS, the results indicate that individuals are willing to pay, on average, 62 cents not to have an additional passenger for commute travel. The corresponding values are \$1.70 for shopping travel and \$1.32 for leisure travel. This WTS to avoid traveling with strangers represents a fixed cost, and is independent of travel time, reinforcing the results from Lavieri and Bhat (2019b) on this front. The ATE results for the trip-level attributes reinforce these VTT and WTS values, but provide additional information regarding the magnitude of pooled RH share changes that can be expected because of changes in times, costs, and number of passengers. Individuals are clearly the most sensitive to travel time for commute trips relative to the other two purposes, while also the least sensitive to the number of additional passengers for the commute purpose. Overall, there is particular scope for promoting dynamic pooled RH, especially for commute trips that continue to contribute most to peak period travel congestion. The VTT and WTS estimates can further be used by TNCs and cities to consider new integrated pooled RH-fixed transit service designs, position traffic congestion alleviation strategies and new mobility services without substantially disturbing the current patterns of active travel/transit ridership, and customize information campaigns to promote pooled RH mode use.

A limitation of our study is the relatively small sample size used in the analysis. This precluded segmenting the RP choice dimension into separate trip purpose categories, though a larger sample size may not have necessarily helped much in this regard given the intrinsically very low share of individuals using the pooled RH service today. Also, we readily admit that the choice behavior results in the current analysis (between the private and pooled RH modes) is likely to be specific to the Austin region. This is because the level of trip attributes (say, average waiting time, average trip cost, availability of pooled RH), or time duration since the introduction of RH, or even the presence of alternative travel modes are likely to vary across regions. Similar analyses using data from other cities in the country and the world would be a fruitful direction for further research. Even so, and as discussed in Section 5.5, the closeness in the value of travel time in the context of the choice of private and pooled RH across different geographical regions (Dallas-Fort Worth in Lavieri and Bhat, 2019b, the Netherlands in Alonso-González *et al.*, 2020a, and Austin in the current study) is quite remarkable.

Of course, the “elephant in the room” is how the current COVID pandemic will impact the inclination to use the pooled RH mode, and more generally any pooled transportation mode (including public transportation). Assessing this will take time; besides, there is likely to be a strong temporal element to the COVID effect. Our expectation is that, in about 3-4 years from now, some semblance of normalcy will be restored in our travel behavior habits. While additional research will be needed to understand how better to position pooling services in the post-COVID future, we feel confident that the results from this analysis will still continue to be valuable and even valid in the longer run. In addition to this important direction for immediate future research, other future research efforts can include a deeper understanding for some of the socio-demographic effects, as reflected in the high direct sub-effects of education and race/ethnicity, as well as the consideration of built environment variables at a finer spatial resolution.

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REFERENCES

- Alba, R. D., Nee, V., 2003. *Remaking the American Mainstream: Assimilation and Contemporary Immigration*. Harvard University Press, Cambridge, MA.
- Alemi, F., Circella, G., Handy, S., Mokhtarian, P. L., 2018. What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California. *Travel Behaviour and Society* 13, 88-104.
- Alonso-González, M. J., Cats, O., van Oort, N., Hoogendoorn-Lanser, S., Hoogendoorn, S., 2020a. What are the determinants of the willingness to share rides in pooled on-demand services? *Transportation*. <https://doi.org/10.1007/s11116-020-10110-2>
- Alonso-González, M. J., van Oort, N., Cats, O., Hoogendoorn-Lanser, S., Hoogendoorn, S., 2020b. Value of time and reliability for urban pooled on-demand services. *Transportation Research Part C* 115, 102621.
- Alonso-Mora, J., Samaranayake, S., Wallar, A., Frazzoli, E., Rus, D., 2017. On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. *Proceedings of the National Academy of Sciences* 114(3), 462-467.
- Angrist, J. D., Imbens, G. W., 1991. Sources of identifying information in evaluation models. *National Bureau of Economic Research Technical Working Paper Series* 117.
- Asmussen, K. E., Mondal, A., Bhat, C. R., 2020. A socio-technical model of autonomous vehicle adoption using ranked choice stated preference data. *Transportation Research Part C* 121, 102835. <https://doi.org/10.1016/j.trc.2020.102835>
- Bain, C. D., Rice, M. L. 2006. The influence of gender on attitudes, perceptions, and uses of technology. *Journal of Research on Technology in Education* 39(2), 119-132.
- Barlow, F.K., Paolini, S., Pedersen, A., Hornsey, M.J., Radke, H.R., Harwood, J., Rubin, M., Sibley, C.G., 2012. The contact caveat: Negative contact predicts increased prejudice more than positive contact predicts reduced prejudice. *Personality and Social Psychology Bulletin* 38(12), 1629-1643.
- Basar, G., Bhat, C.R., 2004. A parameterized consideration set model for airport choice: An application to the San Francisco Bay area. *Transportation Research Part B* 38(10), 889-904.
- Ben-Akiva, M., Lerman, S.R., 1985. *Discrete Choice Analysis: Theory and Application to Travel Demand*, The MIT Press, Cambridge, Massachusetts.
- Ben-Akiva, M., Morikawa, T., 1990. Estimation of switching models from revealed preferences and stated intentions. *Transportation Research Part A* 24(6), 485-495.
- Berkowsky, R. W., Sharit, J., Czaja, S. J., 2018. Factors predicting decisions about technology adoption among older adults. *Innovation in Aging* 1(3), 1-12.
- Bernardo, C., Paleti, R., Hoklas, M., Bhat, C. R., 2015. An empirical investigation into the time-use and activity patterns of dual-earner couples with and without young children. *Transportation Research Part A* 76, 71-91.
- Bhat, C. R., 2015. A new generalized heterogeneous data model GHDM to jointly model mixed types of dependent variables. *Transportation Research Part B* 79, 50-77.
- Bhat, C. R., 2018. New matrix-based methods for the analytic evaluation of the multivariate cumulative normal distribution function. *Transportation Research Part B* 109, 238-256.
- Bhat, C. R., Castelar, S., 2002. A unified mixed logit framework for modeling revealed and stated preferences: Formulation and application to congestion pricing analysis in the San Francisco Bay area. *Transportation Research Part B* 36(7), 593-616.

- Borghans, L., Heckman, J. J., Golsteyn, B. H. H., Meijers, H., 2009. Gender differences in risk aversion and ambiguity aversion. *Journal of the European Economic Association* 7(2-3), 649-658.
- Chevalier, M., Gutsatz, M., 2012. *Luxury Retail Management: How the World's Top Brands Provide Quality Product and Service Support*. John Wiley & Sons, Singapore.
- Correa, T., Hinsley, A. W., de Zúñiga, H. G., 2010. Who interacts on the web?: The intersection of users' personality and social media use. *Computers in Human Behavior* 26(2), 247-253.
- Croson, R., Gneezy, U., 2009. Gender differences in preferences. *Journal of Economic Literature* 47(2), 448-474.
- Dias, F. F., Lavieri, P. S., Garikapati, V. M., Astroza, S., Pendyala, R. M., Bhat, C. R., 2017. A behavioral choice model of the use of car-sharing and ride-sourcing services. *Transportation* 44(6), 1307-1323.
- Erhardt, G. D., Roy, S., Cooper, D., Sana, B., Chen, M., Castiglione, J., 2019. Do transportation network companies decrease or increase congestion? *Science Advances* 5(5), eaau2670.
- Franzen, A., Vogl, D., 2013. Two decades of measuring environmental attitudes: A comparative analysis of 33 countries. *Global Environmental Change* 23(5), 1001-1008.
- Garikapati, V. M., Pendyala, R. M., Morris, E. A., Mokhtarian, P. L., McDonald, N., 2016. Activity patterns, time use, and travel of millennials: A generation in transition? *Transport Reviews* 36(5), 558-584.
- Gerte, R., Konduri, K. C., Eluru, N., 2018. Is there a limit to adoption of dynamic ridesharing systems? Evidence from analysis of Uber demand data from New York city. *Transportation Research Record: Journal of the Transportation Research Board* 2672(42), 127-136.
- Gifford, R., Nilsson, A., 2014. Personal and social factors that influence pro-environmental concern and behaviour: A review. *International Journal of Psychology* 49(3), 141-157.
- Goodspeed, R., Xie, T., Dillahunt, T. R., Lustig, J., 2019. An alternative to slow transit, drunk driving, and walking in bad weather: An exploratory study of ridesourcing mode choice and demand. *Journal of Transport Geography* 79, 102481.
- Heckman, J. J., Vytlacil, E. J., 2000. The relationship between treatment parameters within a latent variable framework. *Economics Letters* 66(1), 33-39.
- Helsper, E. J., Eynon, R., 2010. Digital natives: Where is the evidence? *British Educational Research Journal* 36(3), 503-520.
- Henao, A., Marshall, W. E., 2019. The impact of ride-hailing on vehicle miles traveled. *Transportation* 46(6), 2173-2194.
- Hou, Y., Garikapati, V., Weigl, D., Henao, A., Moniot, M., Sperling, J., 2020. Factors influencing willingness to pool in ride-hailing trips. *Transportation Research Record: Journal of the Transportation Research Board* 2674(5), 419-429.
- Hoy, M. G., Milne, G., 2010. Gender differences in privacy-related measures for young adult facebook users. *Journal of Interactive Advertising* 10(2), 28-45.
- Hu, J., Liu, Y.-L., Yuen, T. W. W., Lim, M. K., Hu, J., 2019. Do green practices really attract customers? The sharing economy from the sustainable supply chain management perspective. *Resources, Conservation and Recycling* 149, 177-187.
- Hyland, M., Mahmassani, H. S., 2020. Operational benefits and challenges of shared-ride automated mobility-on-demand services. *Transportation Research Part A* 134, 251-270.
- ITF, 2017. Shared Mobility Simulations for Helsinki. *International Transport Forum Policy Papers*, No. 39, OECD Publishing, Paris. <https://doi.org/10.1787/3d340a2a-en> [Accessed 07/19/2020].

- JMP, 2020. Statistical Software: JMP Software from SAS. https://www.jmp.com/en_us/software/data-analysis-software.html [Accessed 11/23/2020]
- Kahan, D. M., Braman, D., Gastil, J., Slovic, P., Mertz, C. K., 2007. Culture and identity-protective cognition: Explaining the white-male effect in risk perception. *Journal of Empirical Legal Studies* 4(3), 465-505.
- Kooti, F., Grbovic, M., Aiello, L. M., Djuric, N., Radosavljevic, V., Lerman, K., 2017. Analyzing Uber's ride-sharing economy. *Proceedings of the 26th International Conference on World Wide Web Companion - WWW '17 Companion*, 574-582.
- Lavieri, P. S., Bhat, C. R., 2019a. Investigating objective and subjective factors influencing the adoption, frequency, and characteristics of ride-hailing trips. *Transportation Research Part C* 105, 100-125.
- Lavieri, P. S., Bhat, C. R., 2019b. Modeling individuals' willingness to share trips with strangers in an autonomous vehicle future. *Transportation Research Part A* 124, 242-261.
- Lavieri, P. S., Dias, F. F., Juri, N. R., Kuhr, J., Bhat, C. R., 2018. A model of ridesourcing demand generation and distribution. *Transportation Research Record: Journal of the Transportation Research Board* 2672(46), 31-40.
- Lavieri, P. S., Garikapati, V. M., Bhat, C. R., Pendyala, R. M., Astroza, S., Dias, F. F., 2017. Modeling individual preferences for ownership and sharing of autonomous vehicle technologies. *Transportation Research Record: Journal of the Transportation Research Board* 2665(1), 1-10.
- LeBlanc, S., 2018. Studies are increasingly clear: Uber and Lyft congest cities. Chicago Tribune. Available at: <https://www.chicagotribune.com/business/blue-sky/ct-uber-lyft-congestion-20180225-story.html> [Accessed by: 07/19/2020]
- Lee, Y., Circella, G., Mokhtarian, P. L., Guhathakurta, S., 2020. Are millennials more multimodal? A latent-class cluster analysis with attitudes and preferences among millennial and Generation X commuters in California. *Transportation* 47(5), 2505-2528. <https://doi.org/10.1007/s11116-019-10026-6>.
- Leistner, D. L., Steiner, R. L., 2017. Uber for seniors?: Exploring transportation options for the future. *Transportation Research Record: Journal of the Transportation Research Board* 2660(1), 22-29.
- Li, W., Kamargianni, M., 2020. An integrated choice and latent variable model to explore the influence of attitudinal and perceptual factors on shared mobility choices and their value of time estimation. *Transportation Science* 54(1), 62-83.
- Li, Wenxiang, Pu, Z., Li, Y., Jeff Ban, X., 2019. Characterization of ridesplitting based on observed data: A case study of Chengdu, China. *Transportation Research Part C* 100, 330-353.
- Liang, X., Correia, G. H. de A., An, K., van Arem, B., 2020. Automated taxis' dial-a-ride problem with ride-sharing considering congestion-based dynamic travel times. *Transportation Research Part C* 112, 260-281.
- Liu, N., Yu, R., 2017. Identifying design feature factors critical to acceptance and usage behavior of smartphones. *Computers in Human Behavior* 70, 131-142.
- Lo, J., Morseman, S., 2018. The Perfect UberPOOL: A case study on trade-offs. *Ethnographic Praxis in Industry Conference Proceedings* 2018(1), 195-223.
- Loewenstein, G. F., Weber, E. U., Hsee, C. K., Welch, N., 2001. Risk as feelings. *Psychological Bulletin* 127(2), 267-286. APA PsycArticles.

- Marikyan, D., Papagiannidis, S., Alamanos, E., 2019. A systematic review of the smart home literature: A user perspective. *Technological Forecasting Social Change* 138, 139-154.
- Martinez, L. M., Viegas, J. M., 2017. Assessing the impacts of deploying a shared self-driving urban mobility system: An agent-based model applied to the city of Lisbon, Portugal. *International Journal of Transportation Science and Technology* 6(1), 13-27.
- McGuckin, N., Nakamoto, Y., 2004. Differences in trip chaining by men and women. *Conference proceedings of Research on Women's Issues in Transportation* 35(2), 49-56.
- Moody, J., Middleton, S., Zhao, J., 2019. Rider-to-rider discriminatory attitudes and ridesharing behavior. *Transportation Research Part F* 62, 258-273.
- Moore, M. A., Lavieri, P. S., Dias, F. F., Bhat, C. R., 2020. On investigating the potential effects of private autonomous vehicle use on home/work relocations and commute times. *Transportation Research Part C* 110, 166-185.
- Nair, G. S. and Bhat, C. R., 2020. Sharing the road with autonomous vehicles: Perceived safety and regulatory preferences. *Transportation Research Part C*, forthcoming.
- Nair, G. S., Bhat, C. R., Batur, I., Pendyala, R. M., Lam, W. H. K., 2020. A model of deadheading trips and pick-up locations for ride-hailing service vehicles. *Transportation Research Part A* 135, 289-308.
- Narayanan, S., Chaniotakis, E., Antoniou, C., 2020. Shared autonomous vehicle services: A comprehensive review. *Transportation Research Part C* 111, 255-293.
- Nwankwo, S., Hamelin, N., Khaled, M., 2014. Consumer values, motivation and purchase intention for luxury goods. *Journal of Retailing and Consumer Services* 21(5), 735-744.
- Paleti, R., Eluru, N., Bhat, C. R., 2010. Examining the influence of aggressive driving behavior on driver injury severity in traffic crashes. *Accident Analysis and Prevention* 42(6), 1839-1854.
- Pew Research Center, 2018. Millennials are the largest generation in the U.S. labor force, 2018. <https://www.pewresearch.org/fact-tank/2018/04/11/millennials-largest-generation-us-labor-force/>. [Accessed: 07/23/2020].
- Piao, J., McDonald, M., Hounsell, N., Graindorge, M., Graindorge, T., Malhene, N., 2016. Public views towards implementation of automated vehicles in urban areas. *Transportation Research Procedia* 14, 2168-2177.
- Ramsey, K., Bell, A., 2014. Smart Location Database Version 2.0 User Guide. Available at: https://www.epa.gov/sites/production/files/2014-03/documents/sld_userguide.pdf [Accessed by 07/19/2020]
- Richardson, M., Petrescu, A. and Finch, M., 2016. Event-based ridesharing. United States Patent Application 20160026936. <http://appft1.uspto.gov/netacgi/nph-Parser?Sect1=PTO1&Sect2=HITOFF&d=PG01&p=1&u=/netahtml/PTO/srchnum.html&r=1&f=G&l=50&s1=20160026936.PGNR>. [Accessed: 07/23/2020]
- Rogers, W., Mitzner, T., Boot, W., Charness, N., Czaja, S., Sharit, J., 2017. Understanding individual and age-related differences in technology adoption. *Innovation in Aging* 1(S1), 1026-1026.
- Rowan, M., Dehlinger, J., 2014. Observed gender differences in privacy concerns and behaviors of mobile device end users. *Procedia Computer Science* 37, 340-347.
- Ryu, S., Ho, S. H., Han, I., 2003. Knowledge sharing behavior of physicians in hospitals. *Expert Systems with Applications* 25(1), 113-122.
- Sarriera, J. M., Álvarez, G. E., Blynn, K., Alesbury, A., Scully, T., Zhao, J., 2017. To share or not to share: Investigating the social aspects of dynamic ridesharing. *Transportation Research Record: Journal of the Transportation Research Board* 2605(1), 109-117.

- Schaller, B., 2017. Unsustainable? The growth of app-based ride services and traffic, travel and the future of New York city. Schaller Consulting. Available at: <http://schallerconsult.com/rideservices/unsustainable.htm> [Accessed: 04/15/2020]
- Schwartz, S. H., Rubel, T., 2005. Sex differences in value priorities: Cross-cultural and multimethod studies. *Journal of Personality and Social Psychology* 89(6), 1010-1028.
- Schwieterman, J., Smith, C. S., 2018. Sharing the ride: A paired-trip analysis of UberPool and Chicago Transit Authority services in Chicago, Illinois. *Research in Transportation Economics* 71, 9-16.
- Scott, H., 2003. Stranger danger: Explaining women's fear of crime. *Western Criminology Review* 4(3), 203-214.
- Seçken, N. (2005). The relations between global environmental awareness and technology. *The Turkish Online Journal of Educational Technology* 4(1), 57-67.
- Shocker, A.D., Ben-Akiva, M., Boccara, B., Nedungadi, P., 1991. Consideration set influences on consumer decision-making and choice: issues, models, and suggestions. *Marketing Letters* 2(3), 181-197.
- Solon, G., Haider, S. J., Wooldridge, J. M., 2015. What are we weighting for? *Journal of Human Resources* 50(2), 301-316.
- Spurlock, C. A., Sears, J., Wong-Parodi, G., Walker, V., Jin, L., Taylor, M., Duvall, A., Gopal, A., Todd, A., 2019. Describing the users: Understanding adoption of and interest in shared, electrified, and automated transportation in the San Francisco Bay Area. *Transportation Research Part D* 71, 283-301.
- Stern, P. C., 2000. New environmental theories: Toward a coherent theory of environmentally significant behavior. *Journal of Social Issues* 56(3), 407-424.
- Sudzina, F., 2015. Do gender and personality traits (BFI-10) influence self-perceived tech savviness? *Proceedings of the 18th International Conference on Information Technology for Practice 2015*, 87-94.
- Sundblad, E.-L., Biel, A., Gärling, T., 2007. Cognitive and affective risk judgements related to climate change. *Journal of Environmental Psychology* 27(2), 97-106.
- Swait, J., Ben-Akiva, M., 1987. Incorporating random constraints in discrete models of choice set generation. *Transportation Research B* 21(2), 91-102.
- Tachet, R., Sagarra, O., Santi, P., Resta, G., Szell, M., Strogatz, S. H., Ratti, C., 2017. Scaling law of urban ride sharing. *Scientific Reports* 7(1), 42868.
- Tirachini, A., 2020. Ride-hailing, travel behaviour and sustainable mobility: An international review. *Transportation* 47(4), 2011-2047. <https://doi.org/10.1007/s11116-019-10070-2>
- Tirachini, A., del Río, M., 2019. Ride-hailing in Santiago de Chile: Users' characterisation and effects on travel behaviour. *Transport Policy* 82, 46-57.
- Tirachini, A., Gomez-Lobo, A., 2020. Does ride-hailing increase or decrease vehicle kilometers traveled VKT? A simulation approach for Santiago de Chile. *International Journal of Sustainable Transportation* 14(3), 187-204.
- Triandis, H. C., 2001. Individualism-collectivism and personality. *Journal of Personality* 69(6), 907-924.
- Tscheulin, D. K., 1994. Variety-seeking-behavior bei nicht-habitualisierten Konsumentenentscheidungen. *Zeitschrift für betriebswirtschaftliche Forschung*, 46(1), 54-62.

- U.S. Census Bureau. 2018. American Community Survey 1-Year Estimates. <https://censusreporter.org/profiles/31000US12420-austin-round-rock-tx-metro-area/> [Accessed: 07/19/2020]
- van Buuren, S., Groothuis-Oudshoorn, K., 2011. mice: Multivariate Imputation by Chained Equations in R. *Journal of Statistical Software* 45(3), 1-67.
- Velázquez Romera, G., 2019. *Behavioral factors underlying the adoption of smart mobility solutions*. Doctoral Thesis. ETSI Caminos, Canales y Puertos, Universidad Politecnica de Madrid.
- Vianello, M., Schnabel, K., Sriram, N., Nosek, B., 2013. Gender differences in implicit and explicit personality traits. *Personality and Individual Differences* 55(8), 994-999.
- Wang, C., Jeong, M., 2018. What makes you choose Airbnb again? An examination of users' perceptions toward the website and their stay. *International Journal of Hospitality Management* 74, 162-170.
- Wang, Y., Winter, S. and Ronald, N., 2017. How much is trust: The cost and benefit of ridesharing with friends. *Computers, Environment and Urban Systems* 65, 103-112.
- Ward, C., Raue, M., Lee, C., D'Ambrosio, L., Coughlin, J. F., 2017. Acceptance of automated driving across generations: The role of risk and benefit perception, knowledge, and trust. In M. Kurosu (Ed.), *Human-Computer Interaction*, 254-266. Springer International Publishing.
- Wardman, M., 1988. A comparison of revealed preference and stated preference models of travel behaviour. *Journal of Transport Economics and Policy* 22, 71-91.
- Wenzel, T., Rames, C., Kontou, E., Henao, A., 2019. Travel and energy implications of ridesourcing service in Austin, Texas. *Transportation Research Part D* 70, 18-34.
- Williams, H., Ortuzar, J., 1982. Behavioural theories of dispersion and the mis-specification of travel demand models. *Transportation Research B* 16(3), 167-219.
- Wooldridge, J. M., 1995. Selection corrections for panel data models under conditional mean independence assumptions. *Journal of Econometrics* 68(1), 115-132.
- Zebrowitz, L. A., White, B., Wieneke, K., 2008. Mere exposure and racial prejudice: Exposure to other-race faces increases liking for strangers of that race. *Social Cognition* 26(3), 259-275.

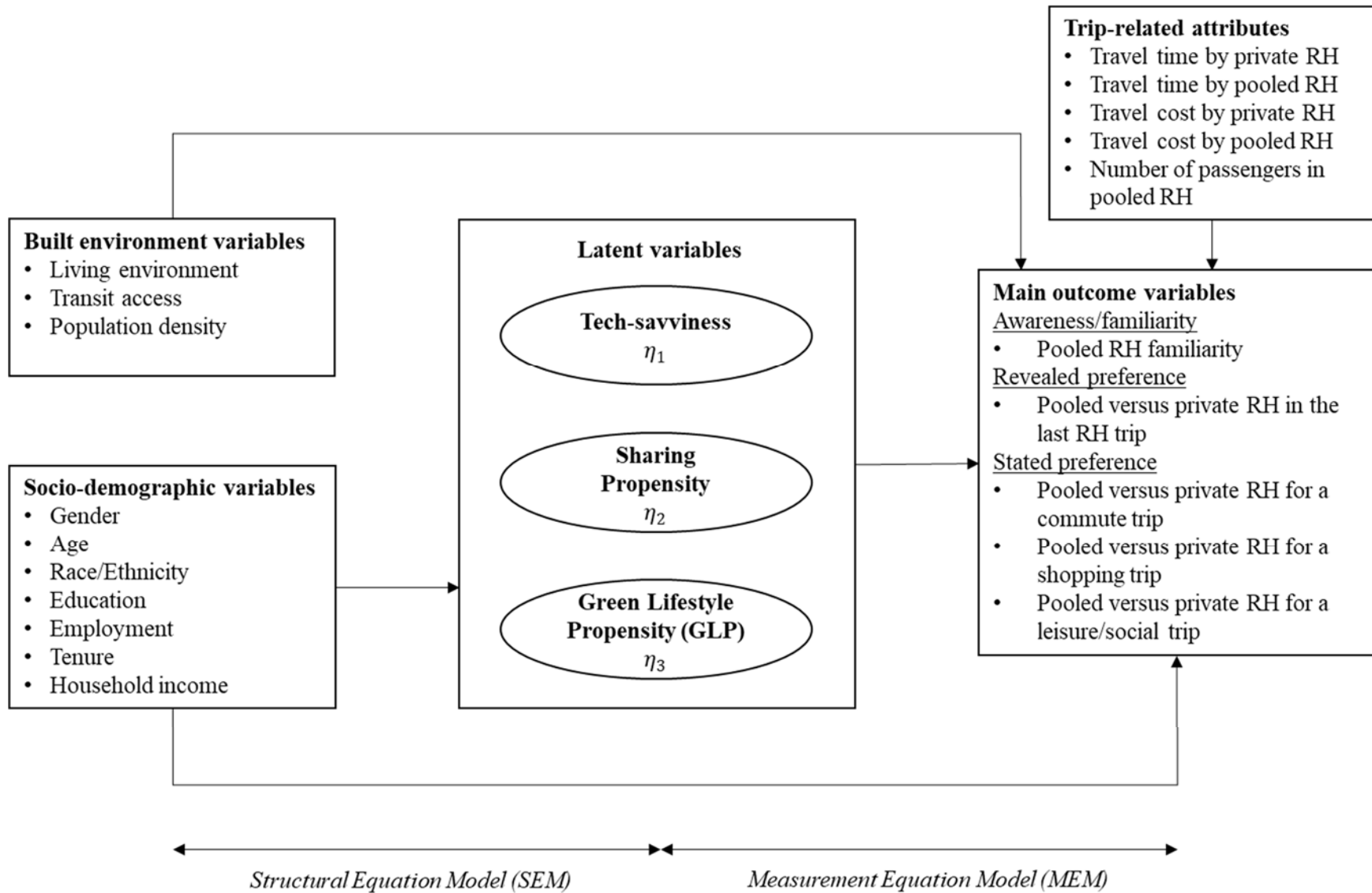


Figure 1. Model Framework

Stated Preference: Attributes and Levels	Private option		Pooled option		
	Travel time [minutes]	Travel cost [\$]	Discount [%]	Additional travel time percentage [%]	Additional passengers
	8	10	20%	25%	1
	13	15	25%	50%	2
18	20	50%	75%	3	
Scenario Example					
Imagine that you call a ride through a smartphone app. For each of the trip purposes below, check whether you would choose the private (Option 1) or shared (Option 2) ridehailing options based on the trip features presented (trip cost, travel time, and the presence of additional passengers). Select only one option in each row. Note that the travel times for shared ridehailing include both your waiting time and the extra time picking up/dropping off other passengers.					
Trip Purpose	Option 1: Private ridehailing		Option 2: Pooled ridehailing		
Commute:	\$18.00	20 minutes	\$12.00	35 minutes	three additional passengers
Shopping:	\$13.00	15 minutes	\$10.00	25 minutes	two additional passengers
Leisure:	\$8.00	10 minutes	\$6.00	15 minutes	one additional passengers

Figure 2. Stated Preference Experiment Components and Scenario Example

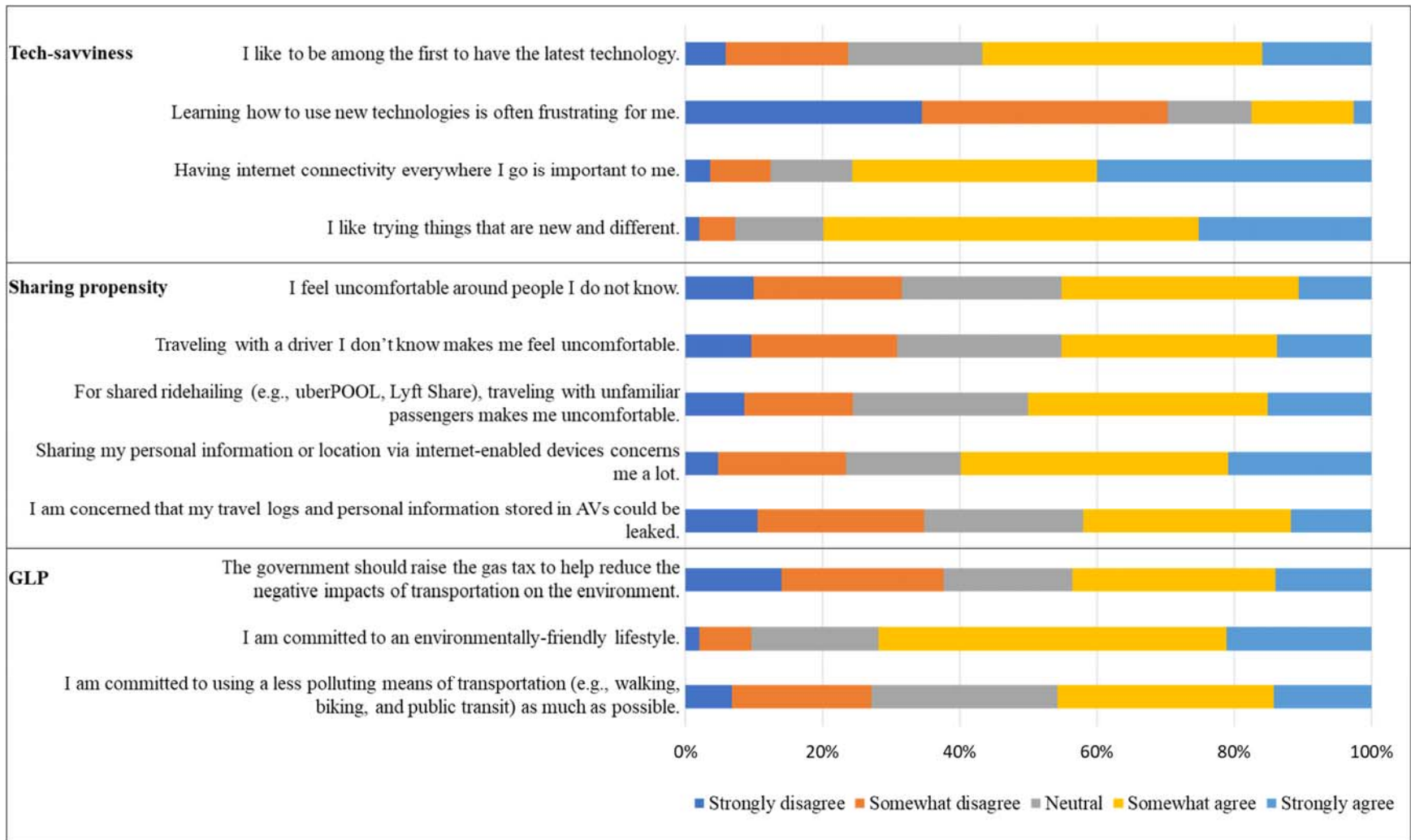


Figure 3. Sample Distribution of Attitudinal Indicators

Table 1. Sample Distribution of Exogenous Variables

Variable	Count	%
Gender		
Female	637	66.8
Male	316	33.2
Age		
18-24	473	49.6
25-54	338	35.5
≥ 55	142	14.9
Race/Ethnicity		
Non-Hispanic, Non-Latino White	484	50.8
Other	469	49.2
Employment Status		
Employed	578	60.7
Not Employed	375	39.3
Education		
Completed high-school or less	134	14.1
Completed some college or technical school	325	34.1
Completed undergraduate degree	327	34.3
Completed graduate degree	167	17.5
Tenure type		
Rent	457	48.0
Own	404	42.4
Other	92	9.6
Household annual income		
Less than \$50,000	375	39.4
\$50,000 - \$99,999	304	31.9
\$100,000 - \$149,999	151	15.8
≥ \$150,000	123	12.9
Land Use (Activity Density)		
Urban	348	36.5
Suburban	484	50.8
Rural	121	12.7
Transit Accessibility		
No transit access within 3/4 miles	541	56.8
Has transit access within 3/4 miles	412	43.2
Population density*		
Medium-to-low	829	87.0
High	124	13.0

* This continuous variable ranges from 0 to 72.3 people per acre (mean=10.6 ppl/acre); a Census Block Group with population density above 20 ppl/acre is characterized as high population density.

Table 2. Sample Distribution of Outcome Variables

Variable	Count	%
Pooled RH familiarity (n=953)		
Familiar with Pooled RH	359	37.67
Not Familiar with Pooled RH	594	62.33
Revealed preference (n=359)		
Private RH	236	65.74
Pooled RH	123	34.26
Stated preference for commute trip (n=347)		
Private RH	180	51.87
Pooled RH	167	48.13
Stated preference for shopping trip (n=359)		
Private RH	117	32.59
Pooled RH	242	67.41
Stated preference for social/leisure trip (n=359)		
Private RH	136	37.88
Pooled RH	223	62.12

Table 3. Estimation Results for the Latent Constructs

Variables (base category)	Tech-savviness		Sharing Propensity		GLP	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Gender (female)						
Male	0.503	4.662	0.490	5.811	--	--
Age (18-54)						
≥ 55	-0.490	-6.850	--	--	--	--
≥ 55 * Male	--	--	--	--	-0.474	-3.004
Race (other races)						
Non-Hispanic/Non-Latino White	--	--	-0.124	-1.602	--	--
Education (≤ undergraduate degree)						
Graduate degree	--	--	--	--	0.227	2.166
Employment (Unemployed)						
Employed	--	--	0.215	2.651	--	--
Household income (< \$150,000)						
≥\$150,000	0.454	3.171	--	--	-0.158	-1.258
Correlations between latent variables						
Tech-savviness	1.000	n/a				
Sharing propensity	0.093	1.676	1.000	n/a		
GLP	0.325	5.529	0.055	1.252	1.000	n/a

Table 4. Estimation Results for the Main Outcomes

Variables (base category)	Pooled RH familiarity (base: not familiar with pooled RH)		RP: Pooled RH (base: private)		SP commute: Pooled RH (base: private)		SP shopping: Pooled RH (base: private)		SP social/leisure: Pooled RH (base: private)	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
<i>Latent variables</i>										
Tech-savviness	--	--	-0.737	-6.023	-0.183	-1.683	-0.546	-3.639	-0.737	-6.023
Sharing propensity	0.288	5.091	0.146	1.631	0.230	2.426	0.302	2.743	0.146	1.631
GLP	--	--	0.421	4.238	0.179	1.716	0.236	1.867	0.421	4.238
<i>Socio-demographics variables</i>										
Age (18-24)										
25 to 54	-0.260	-2.366	--	--	--	--	--	--	--	--
≥ 55	-1.121	-4.810	--	--	--	--	--	--	--	--
Race (other races)										
Non-Hispanic/Non-Latino White	-0.170	-1.649	-0.367	-2.040	--	--	--	--	--	--
Education (high-school or less)										
>High-school	0.337	2.386	0.592	1.989	--	--	--	--	--	--
Tenure (own or other)										
Rent	0.473	4.291	--	--	--	--	--	--	--	--
Household income (< \$150,000)										
≥\$150,000	0.262	1.786	--	--	--	--	--	--	--	--
<i>Built environment variables</i>										
Living environment										
Urban/suburban	0.590	-3.136	--	--	--	--	--	--	--	--
Transit access (no transit access)										
Has transit access	0.291	2.571	--	--	--	--	--	--	--	--
Population density (≤20 ppl/acre)										
High	--	--	0.454	1.915	--	--	--	--	--	--
<i>Trip Level attributes</i>										
Travel time [10s of minutes]	n/a	n/a	n/a	n/a	-0.595	-2.811	-0.599	-2.605	-0.407	-1.748
Travel cost [10s of dollars]	n/a	n/a	n/a	n/a	-1.286	-4.138	-1.857	-5.192	-2.273	-6.209
Additional passenger	n/a	n/a	n/a	n/a	-0.080	-0.871	-0.315	-2.927	-0.299	-2.607
Constant	-0.495	-3.249	-0.931	-2.991	0.015	0.055	0.942	3.076	0.609	1.943

Table 5. Comparison of Disaggregate Goodness-of-fit Between GHDM and IBP Models

	GHDM	IBP
No. of observations	953	953
No. of parameters	65	51
Average probability of correct prediction	0.0859	0.0773
Predictive log-likelihood at convergence $L(\hat{\theta})$	-1381.793	-1419.285
Predictive log likelihood of base (independent market share) model $L(c)$		-1575.456
Predictive Adjusted Likelihood Ratio Index	0.082	0.067

Table 6. RP-Anchored Trip-Purpose Specific Estimates

Variables (base category)	Pooled RH familiarity (base: not familiar with pooled RH) Coeff.	RP-SP commute: Pooled RH (base: private) Coeff.	RP-SP shopping: Pooled RH (base: private) Coeff.	RP-SP social/leisure: Pooled RH (base: private) Coeff.
<i>Latent variables</i>				
Tech-savviness	--	-0.870	-0.930	-0.737
Sharing propensity	0.288	0.172	0.184	0.146
GLP	--	0.497	0.531	0.421
<i>Socio-demographics variables</i>				
Age (18-24)				
25 to 54	-0.260	--	--	--
≥ 55	-1.121	--	--	--
Race (other races)				
Non-Hispanic/Non-Latino White	-0.170	-0.434	-0.464	-0.367
Education (high-school or less)				
>High-school	0.337	0.700	0.748	0.592
Tenure (own or other)				
Rent	0.473	--	--	--
Household income (< \$150,000)				
≥\$150,000	0.262	--	--	--
<i>Built environment variables</i>				
Living environment (rural)				
Urban/suburban	0.590	--	--	--
Transit access (no access)				
Has transit access	0.291	--	--	--
Population density (≤20 ppl/acre)				
High	--	0.536	0.573	0.454
<i>Trip Level attributes</i>				
Travel time [10s of minutes]	n/a	-0.595	-0.599	-0.407
Travel cost [10s of dollars]	n/a	-1.286	-1.857	-2.273
Additional passenger	n/a	-0.080	-0.315	-0.299
Constant	-0.495	-1.442	-0.517	-0.855

Table 7. ATE for Pooled RH: Commute Purpose

Variable	Base Level	Treatment Level	% Contribution by mediation through						Overall ATE
			Pooled RH familiarity direct effect	Pooled RH familiarity sharing propensity increase	Tech-savviness decrease	Sharing propensity increase	GLP increase	Pooled RH choice direct effect	
Pooled RH interest for the commute purpose									
<i>Socio-demographic</i>									
Gender	Female	Male	0	39	-26	31	-4	0	0.023
Age	18-24	55+	-77	0	20	0	-3	0	-0.144
Race/ethnicity	Other races	Non-Hispanic/Non-Latino White	-24	-9	0	-5	0	-62	-0.083
Education	High school or less	Graduate degree	47	0	0	0	3	50	0.117
Employment	Unemployed	Employed	0	62	0	38	0	0	0.016
Tenure	Own or other	Rent	100	0	0	0	0	0	0.073
Household income	< \$150,000	≥ \$150,000	70	0	-27	0	-3	0	0.022
<i>Built environment</i>									
Living environment	Urban/suburban	Rural	-100	0	0	0	0	0	-0.084
Transit access	Transit access	No transit access	-100	0	0	0	0	0	-0.044
Population density	Low	High	0	0	0	0	0	100	0.045
<i>Trip level attributes</i>									
Travel time	Current time	Decrease by 5 mins	-	-	-	-	-	100	0.039
Travel cost	Current cost	Decrease by \$1	-	-	-	-	-	100	0.017
Additional passenger	Current scenario	1 additional passenger	-	-	-	-	-	-100	-0.011