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A Socio-Technical Model of Autonomous Vehicle Adoption Using Ranked Choice Stated Preference Data

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A Socio-Technical Model of Autonomous Vehicle Adoption Using Ranked Choice Stated Preference Data

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Abstract

A Socio-Technical Model of Autonomous Vehicle Adoption Using Ranked Choice Stated Preference Data

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Understanding the "*if*" and "*when*" of autonomous vehicle (AV) adoption is of clear interest to car manufacturers in their positioning of business processes, but also to transportation planners and traffic engineers. In this thesis, we examine the individual-level AV adoption and timing process, considering the psycho-social factors of driving control, mobility control, safety concerns, and tech-savviness. A ranked choice stated preference design is used to elicit responses from Austin area residents regarding AV adoption. Our results underscore the need to examine the adoption of technology through a psycho-social lens. In particular, technology developments and design should not be divorced from careful investigations of habits and consumption motivations of different groups of individuals in the population. The findings from our analysis are translated to specific policy actions to promote AV adoption and accelerate the adoption time frame.

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Chapter 1: Introduction[1]

Autonomous vehicle (AV) technology is now well within the realm of thinkable possibility and is rapidly advancing as a distinct transportation market reality of the near future. [2] Cars with near-fully automated vehicles are now expected to be available for public consumption by the mid to late 2020s. Fully autonomous vehicles or AVs (with no need for any human intervention) are expected to be available in the marketplace by the mid-2030s (Anderson, 2020). Of course, introduction into the marketplace, by itself, does not determine how quickly AVs will be purchased and used by consumers. On the demand side, penetration will depend on consumers' acceptance of this new technology, and how quickly this happens. These "*if*" and "*when*" dimensions of AV adoption are of clear interest to car manufacturers, as they assess profit margins and consider modifications to their medium-to-long term supply chain protocols. But it also is of substantial interest to transportation planners and traffic engineers. After all, the adoption

[1] 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. Conducted the writing, analysis, and modeling for this paper.

[2] There has been substantial discussion in the literature about the terminology of autonomous versus automated vehicles. The label "Automated vehicles" is a general term that includes autonomous vehicles as a special case. Thus, for example, many vehicles even today may be labeled as "automated", in the sense that at least for specific parts of a journey and specific driving tasks, the human may be dispensed with transiently. For example, a human driver on a highway may set the vehicle to cruise control mode, which essentially maintains the vehicle at a desired speed without the need for the driver to be having a foot on the gas pedal. The label "Autonomous vehicle", on the other hand, refers to a vehicle that pretty much takes over the entire driving task for the entire journey, with the human driver simply providing guidance instructions (such as origin/destination points) or routing desires (no tolls or taking a scenic route or instructing the computer to take a specific desired route). Autonomous vehicles correspond to a high level of artificial intelligence involvement and literally zero human involvement in the driving task. In the survey used in the analysis of the current study, autonomous vehicles are defined in a general and non-technical fashion as "cars and trucks that can operate on their own without a human driver." Formally, such a description would correspond to an automation level of 4 or above according to the SAE description of levels of automation (SAE International, 2018). In the rest of the thesis, we will consistently use the term AVs to refer to autonomous vehicles.

rate of AVs in the short, medium, and long range is central to the study of AV impacts on mobility and is a key component of transportation planning (see, for example, Guerra, 2016 and Dias *et al.*, 2020). Indeed, understanding and predicting the potential impacts of AV technologies on household vehicle ownership and use, individual activity-travel behavior, and job-housing choices is critical to land use and transportation systems planning (Mahmassani *et al*., 2018).

The goal of this thesis is to further the understanding of the individual-level factors that contribute to AV adoption (AVD) and duration to adoption (DAD) (the *if* and *when* dimensions of adoption). Individual socio-demographics as well as psycho-social variables (in the form of latent psychological constructs) are used as determinant variables, while acknowledging the potential endogeneity of these psycho-social variables to the AVD and DAD decisions. A multivariate model accommodating a total of seven variables, including a mix of continuous variables, a ranked variable, and a nominal variable, is estimated. Based on the model results, we propose policy measures that could make individuals more amenable to adopting AVs quickly. The study uses data from an Austin-based survey on new mobility services conducted by the authors as part of a multi-city survey.

The rest of this thesis is organized as follows. Section 2 provides a brief overview of past literature of individual-level models relevant to understanding the AVD and DAD decisions. Section 3 presents the survey administration process, data preparation steps, and the analytic framework. Section 4 presents the model estimation results and goodness of fit measures. Section 5 discusses policy implications to accelerate AV adoption. Finally, Section 6 concludes the thesis with a summary discussion of the important findings, along with an identification of future research directions.

Chapter 2: Literature Review[3]

There is a growing body of literature devoted to the study of the adoption and impacts of transformative technologies in transportation, including AVs and mobility-on-demand services (such as car-sharing and ride-hailing). In the future, there is likely to be a convergence of these, as mobility-on-demand services increasingly use AVs for providing transportation. Due to this likely overall convergence toward AVs, there has been substantial recent literature focusing on the potential changes in transportation system performance in an AV future, including possible impacts of AV technology on highway capacity (Simko, 2016; Meyer *et al*., 2017), work and home location choices (Zhang and Guhathakurta, 2018; Moore *et al*., 2020), parking and infrastructure design (including curb design considerations for drop-off/pick-up and traffic lane/median design; see Zhang *et al*., 2015; Henaghan, 2018), roadway safety effects (see, for example, Litman, 2020; Haboucha *et al*., 2017; Rasouli and Tsotsos, 2020), and general impacts on activity-travel behavior (see, for example, Childress *et al*., 2015; Kröger *et al*., 2016, Dias *et al*., 2020). Some of these studies do consider the difference between private AV ownership and the use of mobility-on-demand shared AV (SAV) services (ride-hailing/rental fleet services operated by mobility companies) when investigating potential AV effects on land-use and activity-travel behavior, while many do not. Some recent papers have also produced reviews of studies focused on potential AV impacts (see Hawkins and Nurul Habib, 2019; Soteropoulos *et al*., 2019; Gkartzonikas and Gkritza, 2019; Dias *et al*., 2020).

[3] 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. Conducted the writing, analysis, and modeling for this paper.

One issue that comes through clearly from the reviews listed above is that most studies attempting to understand AV effects on travel behavior and land-use are based on simulations using *a priori* assumptions related to AV market adoption and user acceptance (based on, for example, macro-predictions of AV adoption rates and fleet penetrations). In the past few years, there has been an increasing emphasis on studying the AV adoption process itself. The relatively early literature in this area examined adoption rates as a function of sociodemographic variables and technology features (such as lane-keeping, parking assistance, automatic braking, and entertainment applications; see Howard and Dai, 2014 and Schoettle and Sivak, 2014). Much of this research was based on descriptive analysis (Silberg *et al*., 2013; Vallet, 2013; Payre *et al*., 2014), though some early studies used structural equation models or discrete choice models (see Shin *et al*., 2015; Abraham *et al*., 2016). More recently, there has been an increased recognition of the importance of attitudinal and lifestyle factors in influencing the AVD decision, including (a) tech-savviness (Zmud and Sener, 2017; Lavieri and Bhat, 2019a), (b) green lifestyles (Haboucha *et al*., 2017; Lavieri *et al*., 2017), (c) privacy and security concern (Zmud *et al*., 2016; Lavieri and Bhat, 2019a,b), (d) safety perceptions (Kaur and Rampersad, 2018; de Miguel *et al*., 2019; Moody *et al*., 2020), (e) interest in the productive use of travel time (Lavieri and Bhat, 2019b; Moore *et al*., 2020) and (f) variety-seeking lifestyle (Alemi *et al*., 2018; Lavieri and Bhat., 2019a). As in the case of assessing AV impacts on activity-travel behavior, many of these earlier studies do not, however, differentiate between the adoption paradigms/configurations of private AV vehicle ownership versus SAV system use. Concepts of adoption paradigm and configuration refer to patterns of consumer behavior in choosing to use an AV, and whether this use is through purchasing an AV or relying on AV ride-hailing services. To our knowledge, only a handful of studies examine the adoption paradigm, including

Zmud and Sener (2017) and Lavieri *et al*. (2017). This is despite the fact that the impacts of AV technology on the transportation system are likely to be very different depending on the AV usage paradigm that prevails in the market.

In addition to the limited attention on the paradigm/configuration of AV adoption (AVD), there is also relatively little attention accorded in the literature to the duration to adoption (DAD) dimension of choice, a critical issue in being able to project AVD rates over time. This is particularly important because of the typical S-curve pattern observed in the uptake of most technological innovations, with the early adopters and the late adopters (the "laggards") occupying the flat portions of the curve (see Liljamo *et al*., 2018). Understanding and distinguishing the characteristics of individuals in these two extreme groups (and those who fall somewhere in-between) is important to position information and safety campaigns to accelerate the acceptance/adoption of AVs and bring them into the mainstream, particularly, if possible, in the SAV mode of operation.

2.1 THE CURRENT THESIS

The current study is motivated by the need to better understand AVD and DAD decisions. There are several salient aspects of the thesis. First, we differentiate between private AV ownership and SAV use. Related to this point is that we also present the question regarding AV adoption in the "tight" context of the next vehicle purchase occasion, with three possible response options: (a) purchase a regular vehicle, (b) purchase an AV, and (c) not purchase a vehicle and use SAV services. Tying the question to the next vehicle purchase occasion provides a level of choice time-frame specificity for respondents. It also provides a better sense of vehicle turnover (as opposed to a generic question of whether an individual will purchase an AV or not), as well as allows us to examine the trade-offs between fixed costs (that impact RV and AV purchase, but not

SAV use) and variable costs (that influence all three of the AVD alternatives). Second, we also consider the DAD dimension, even if admittedly rather coarsely in the three nominal categories of (a) I will never buy an AV, (b) I will be one of the first people to buy an AV, and (c) I will eventually buy an AV, but only after these vehicles are in common use. Third, we model the AVD and DAD dimensions jointly, to acknowledge the possibility that one or more attitudes/lifestyle traits may, at once, influence both these dimensions. These attitudes/lifestyle traits are not directly observed and include an unobserved component (that cannot be explained by individual observed attributes). That is, these traits are stochastic latent constructs, and thus the impact of such a latent construct simultaneously on both AVD and DAD leads to jointness due to the stochasticity embedded in the construct. For example, an individual who has an intrinsically elevated safety concern with AVs is expected to be more likely to buy a regular vehicle at the next purchase occasion (along the AVD dimension) and be very unlikely to be a first-buyer of AVs (along the DAD dimension) even if purchasing AVs at some point. Fourth, in addition to two constructs that have been widely used in the AVD literature (associated with safety concerns and tech-savviness), we also consider two psychological constructs that have received limited to no attention in the AV adoption literature: driving control and mobility control (see Gkartzonikas and Gkritza, 2019 and Voinescu *et al*., 2020 for good reviews of studies that consider personality traits, from which it is clear that driving control and mobility control have rarely been used to explain AVD and DAD decisions). On the other hand, earlier information science and identity-based consumer behavior literature on technology adoption has identified the need for "control" over life events as being negatively associated with the adoption of new assisting technologies (Leung *et al*., 2018; Marikyan *et al*., 2019). This is because the need to be in control is positively associated with mental self-esteem and provides a sense of self-identity, while “succumbing” to assistive technology is associated with a loss in self-identity. In other words, those who identify strongly with driving will resist technology that usurps that human skill away in what can be viewed as “cheating” (other reasons for the effects of control variables on the AVD and DAD decisions are discussed in Section 3.2.2). Thus, those who intrinsically feel a need for driving control are likely to buy a regular vehicle in their next purchase occasion, while those with a need for mobility control may prefer a privately owned vehicle (AV or regular) rather than eschew private ownership altogether in favor of SAV use. Fifth, we consider the latent constructs themselves as being potentially endogenous to the main outcome variables of AVD and DAD by allowing correlation effects between the stochastic terms embedded in the latent constructs and the error terms of the main outcome equations. Doing so is important because the AVD and DAD choices will generally be influenced by multiple unobserved lifecycle and lifestyle factors that may also influence the psycho-social variable. For example, the presence of a special needs child in the household may lead to an elevated “safety” concern with AVs, not really because of safety concerns with AV technology per se but more with the need to be available as a helping hand for the child (as we indicate later, in our analysis, whether or not an individual is comfortable with an AV transporting a child is used as an indicator to construct the AV safety concern latent construct). Thus, individuals in households with special needs children may generically be pre-disposed to forego AVs. Of course, AV safety concern is likely also to have a “true” impact on preferring a regular vehicle rather than an AV. But if the former intrinsic disinclination for an AV (that is, inclination for a regular vehicle to chauffeur children with special needs) is ignored, this can exaggerate the latter “true” negative (positive) effect of AV safety concern on AV purchase (RV purchase). This is not simply an esoteric econometric issue, but has relevance to tease out the “true” effects of the latent constructs for designing informed policies. In particular, ignoring such endogeneity can lead to the incorrect estimation of the latent construct effects on the main outcome variables, which can then lead to the incorrect estimation of the effect of socio-demographic variables mediated through the latent constructs (and to mis-informed policy actions). Sixth, and related to the fifth point, we go beyond simply considering the effects of psycho-social factors in estimation and translate the model results in a way that provides important insights for policy making. We do so by partitioning the influence of a socio-demographic variable into a direct effect and also indirect mediating effects through the psycho-social constructs. This allows for the identification of the most effective targeting and positioning strategies, customized to each socio-demographic group of the population. Finally, from a methodological standpoint, this study, to our knowledge, is the first instance of a joint mixed model that includes multiple continuous variables, as well as a nominal variable and a ranked variable (respondents were asked to rank the three AVD options, rather than only provide their first-choice).

Chapter 3: Methodology[4]

3.1 THE SURVEY

The data used in the analysis in this thesis was collected as part of a larger "emerging mobility" on-line web survey conducted in the Austin metropolitan area in Texas in 2019. 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 (sample representativeness issues are discussed in Section 3.2.1).

[4] 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. Conducted the writing, analysis, and modeling for this paper.

A financial incentive was provided in the form of $10 Amazon gift cards for the first 250 respondents, while the remaining respondents were entered into a drawing to win one of the remaining one hundred $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 1,021, after removing 106 respondents who did not respond to one or both of the AV adoption (AVD) or duration to adoption (DAD) questions.

The survey itself sought information on individual and household socio-demographics, general attitudinal/life-style perspectives as well as AV-specific attitudinal perspectives, and stated preferences related to the adoption and use of a suite of emerging mobility options, including AVs. Individual and household socio-demographics included variables related to age, gender, employment status, education level, driver's license holding, household annual income, household size, number of children in the household, and number of vehicles currently owned. The attitudinal perspectives were obtained by posing a series of attitudinal statements, and eliciting responses by asking respondents to choose the category that most closely matches their feelings; the attitudinal responses themselves were captured using a five-point Likert-scale from "strongly disagree" to "strongly agree".

As stated earlier, there are two dimensions of interest in the current thesis, with the AVD stated choice questions having three possible alternatives: (a) purchase a regular vehicle, (b) purchase an AV, and (c) not purchase a vehicle and use SAV services. For brevity, in the rest of this thesis, we will refer to these three alternatives as RV, AV, and SAV. The DAD stated intention question also has three alternatives: (a) I will never buy an AV, (b) I will be one of the first people to buy an AV, and (c) I will eventually buy an AV. For ease in presentation, we will abbreviate these alternatives as never buy (NB), first-to-buy (FB), and eventually buy (EB). In the survey, the AVD decision was framed as two stated choice questions based on an experimental design, while the DAD decision was a simple question of "when do you expect to buy an AV". For the AVD experimental design, considering the uncertainties associated with the AV future, we used simple scenarios characterized by three vehicle/service attributes. These are: (1) fixed cost per month associated with RV and AV (with zero fixed cost for the SAV alternative), (2) variable travel cost per mile, structured in a way that the SAV cost is always higher than that for the RV and AV alternatives, and (3) average wait time associated with the SAV service (with zero wait time for RV and AV alternatives). The attributes and their respective levels, as well as a sample of the actual AVD ranking question, are presented in Appendix A. The attribute levels were defined with the objective of keeping the scenarios realistic, while also providing an instrument to engender adequate variability in the attribute values across scenarios.[5] In all, there were of the order of 1,944 possible combinations of the attribute levels. From these combinations, 18 different scenarios were chosen using an orthogonal fractional factorial design with the focus on isolating main effects and keeping orthogonality. Each individual was randomly assigned to respond to two scenarios, given the survey was already very lengthy and obtained information on not only AVs, but also micro-mobility and ride-hailing use patterns.

An important departure from traditional SP choice design is that we use a ranking preference elicitation approach for the AVD decision, rather than the typically used first-choice preference elicitation approach. This is because much more information can be obtained on choice alternative valuations from the ranking approach than the first-choice approach, as recently demonstrated by Nair *et al*. (2018) and Nair *et al*. (2019). Further,

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[5]The cost structures for regular vehicles were based off estimates from the U.S. Bureau of Labor Statistics (2018), that estimated fixed costs at about $330 per month and variable costs at about 35 cents per mile. Similar cost structures were assumed for an AV. For SAV, the variable cost structure was based off current ride-hailing estimates plus a premium cost; see Bösch *et al*., 2018 and Narayanan *et al*., 2020).

these two studies also show through simulation exercises that the prevailing view of the ranking elicitation mechanism in the econometrics literature as being unreliable (ostensibly because of progressively higher cognitive demands placed on individuals when ranking less preferred alternatives) is completely misplaced. This unfortunate view can actually be traced to the typical use of a rank-ordered logit (ROL) specification, which has specific properties that inevitably lead to such an inappropriate conclusion about the veracity of the ranking preference elicitation mechanism. On the other hand, the rank-ordered probit (ROP) constitutes a more appropriate and flexible behavioral structure to deal with rank-ordered data (this difference is not the same as the difference between a multinomial probit model and a multinomial logit model in the context of first-choice data analysis, but much more dramatic; conceptually speaking, the ROL model is an "impossible" structure for ranking data analysis, based on Luce and Suppes's (1965) impossibility theorem). At the same time, recent advancements in analytical methods to accurately and quickly evaluate the cumulative multivariate normal distribution functions make the estimation of an ROP model very tractable for practice. Also, rank-ordered data is as easy to collect as the most preferred alternative, and also has the distinct advantage of being more cost-effective for a specified precision level of parameters than purely choice (or first preference) data surveys.

3.2 ANALYTIC FRAMEWORK AND DATA DESCRIPTION

The analytic framework focuses on understanding the inter-relationship between the AVD and DAD choice decisions, while considering individual-level variables (individual demographics and household characteristics) as well as attitudes/lifestyle factors (also referred to as psycho-social factors). These psycho-social factors are not directly observed, and so are viewed as latent stochastic constructs manifested through a suite of observed indicators. In the current study, four such latent constructs are used (the reasoning for the use of these four specific psycho-social factors is discussed later): (1) (need for) driving control, (2) (need for) mobility control, (3) concerns with AV safety (safety concern), and (4) an individual's technology-savviness (tech-savviness).

Figure 1 provides a diagrammatic representation of the analytic framework, where we suppress the indicators of each latent construct to avoid clutter. The vehicle/service attributes in the choice experiment influence the AVD main outcome. Individual-level characteristics influence the latent constructs, and both the individual-level characteristics and the latent constructs affect the AVD and DAD main outcomes. Thus, the individual-level characteristics have both a direct effect on the main outcomes as well as an indirect effect (through the mediating role of the latent constructs). Unlike many earlier studies using latent constructs, we allow the latent constructs themselves to be co-endogenous with the AVD and DAD main outcomes, for reasons discussed earlier in Section 2.1 (that is, we allow correlations between the latent constructs and the two main outcomes of interest). This is illustrated in Figure 1 by the double-headed arrow between the latent construct box and the main outcome box. Further, if a stochastic latent construct impacts more than one alternative within each of the main outcomes, a covariance is engendered across the impacted alternatives for the outcome (because of the error term embedded within the latent construct). Similarly, if a latent construct impacts an alternative in the AVD main outcome as well as an alternative in the DAD main outcome, this immediately generates a covariance across the AVD and DAD outcomes.

The vehicle/service attributes for the SP choice experiment have already been discussed earlier. Each of the rest of the elements of Figure 1 is discussed in turn in the next three sections.

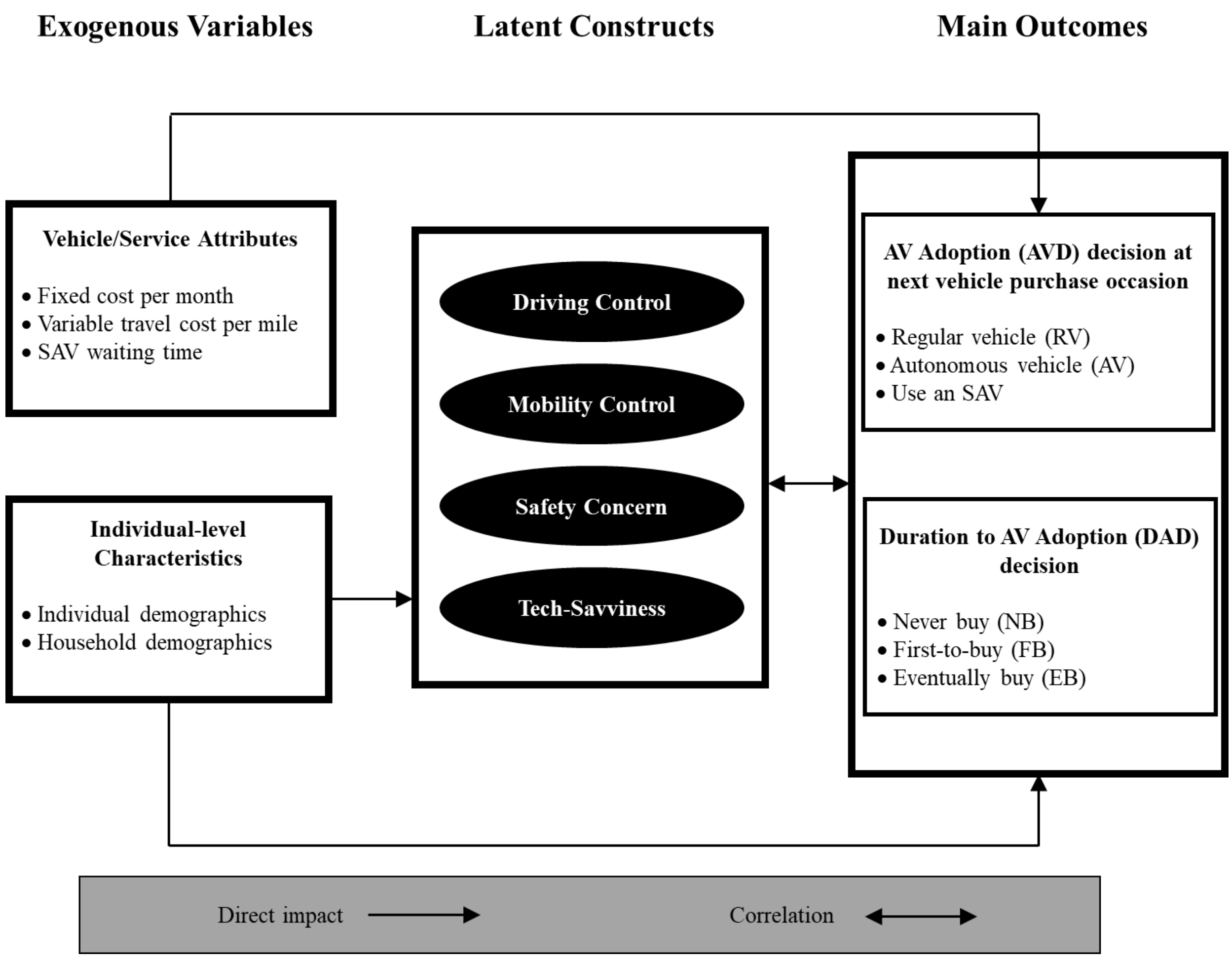

Figure 1. Analytic Framework

3.2.1 Individual-level Characteristics

The convenience sample collected in our survey shows an over-representation of young individuals, women, and more highly educated and low-income individuals (please see Appendix B for a detailed discussion and presentation of the sample demographic characteristics and comparison with the census population statistics of the Austin-Round Rock, TX Metro Area, as estimated by the U.S. Census Bureau, 2018). While the over-representation of women in our sample is interesting, the skew in the other variables is to be expected. The Austin region is home to many colleges and universities; students who study at these higher education institutions may not consider the area their main place of residence. If only renting property or living in Austin to attend school for nine months out of the year, students may not report themselves as Austin residents in the Census. On the other hand, a high number of students responded to our survey (about 52% of the total respondent pool).

The sample skew obviously implies that descriptive statistics for the endogenous variables of interest in this thesis cannot be generalized to the Austin area adult population. However, the focus of the current thesis is on estimating causal effects (how changes in exogenous demographics and psycho-social factors impact the endogenous variables of interest). In such causal analyses, the issue to weight or not to weight is primarily determined by whether the sampling is dependent or independent of the dependent variables conditional on the explanatory variables. In particular, weighting is needed for consistent estimation of the causal relationship if the sampling strategy is endogenous to the modeled outcomes but is not needed if the variation in the sampling rate is based on exogenous variables. In our case, the sampling strategy was not based on the endogenous variables, and so our sample corresponds to the case of exogenous sampling. In this situation, the unweighted approach is the preferred one because it is more efficient (provides more precise parameter estimates). Thus, in our model estimations, we use the unweighted approach. The reader is referred to Wooldridge (1995) and Solon *et al*. (2015) for an extensive discussion of this point. In addition, our sample displays adequate variation across the range of values of each socio-demographic variable, allowing us to test a variety of functional forms for the effects of these variables. Overall, the combination of our exogenous sampling approach, as well as the adequate variation in the sample to test demographic effects at a fine level of resolution, implies that there is no reason to believe that the individual level relationships estimated from disaggregate models developed in this thesis are not applicable to the larger population.

3.2.2 Stochastic Latent Constructs

In the structural equations model component of the analytic framework, individual-level characteristics (left side of Figure 1) are used to explain the four latent constructs representing driving control, mobility control, safety concern, and tech-savviness. Other latent constructs for security concern, green lifestyle, time sensitivity, privacy sensitivity, and variety-seeking were also constructed 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 thesis. For example, a key indicator for safety concerns came out to be the worry about technology failure considerations. This worry directly correlates with what turned out to be a key indicator for security concerns in the form of the worry about potential security breaches through which important personal information becomes public.[6] But, to a much larger extent, many other psycho-social constructs faded away because the need for driving control and mobility control appear to be the dominant psycho-social factors impacting AV adoption and duration-to-adoption considerations. On the other hand, most earlier studies of AV adoption (and even the broader technology adoption literature) do not consider such affective emotions (see Voinescu *et al*., 2020 and Gkartzonikas and Gkritza, 2019). Considering these control-related psychological factors within a rigorous

[6] Of course, we readily admit that this correlation is also a simple reflection of our wording in the survey instrument. For example, the indicator just discussed about safety concerns was worded as "I am concerned about the potential failure of AV sensors, equipment, technology, or programs". There is some ambiguity in this wording, because it does not differentiate between technology failures that may lead to a traffic safety problem and failures that may lead to security breaches. More generally, it would be helpful for the transportation community to develop a standard battery of indicator questions related to each possible psycho-social construct, as a way to avoid ambiguity.

AV adoption and timing modeling framework is a unique contribution of our study (Nordhoff *et al*., 2016, Charness *et al*., 2018, and Musselwhite, 2019 also consider driving control in the context of "sensation-seeking and "willingness to relinquish driving control", but these are rather descriptive studies and they do not consider mobility control).[7]

The first latent construct, driving control, describes an individual's urge/need to remain in control of driving themselves around. The social-psychological literature shows a clear relationship between the need to be in control in general and compulsive/habituated behavior. In fact, those with an obsessive-compulsive personality are, among other things, exemplified by a preoccupation over control of their environment (Borg, 2018). This is because a change in their habituated environment brings anxiety. Anxiety bypasses any considerations of the need to gather more information, and gets immediately translated into vehement opposition to the change. Fundamentally, for such individuals, trying to control the environment serves as a coping mechanism to retain sanity in what may seem an out of-control external world. As indicated earlier, and related to this issue of a coping mechanism, driving control can also serve as an important self-identity retention tool. The strong need for driving control, therefore, can be viewed as being associated with a reluctance to give up self-driving.

[7] Interestingly, emotive factors (such as need for control or anxiety) have not been adequately considered in traditional psychosocial models, such as the Theory of Planned Behavior (TPB; Ajzen, 1991), which focuses more on attitudes toward a behavior (such as safety benefits and privacy/security concerns), subjective norms (what people around think of a specific viewpoint), and perceived behavior control (but more whether a new product/technology is within the skill set for use by an individual, rather than an intrinsic control-oriented personality trait). Similarly, the traditional Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh and Davis, 2000) focuses on perceived usefulness and perceived ease of use but not antecedent awareness or emotive considerations, as indicated by Piao *et al*. (2016), Ward *et al*. (2017) and Marikyan *et al*. (2019) in the socio-technical literature. Here, we attempt to strengthen the TPB and TAM frameworks by adding control as another construct, while retaining some of the other constructs (including safety concerns and tech-savviness levels) that fall within the purview of one or both of the TPB and TAM frameworks (see also Rahman *et al*., 2017).

Driving control-inclined respondents may also want to retain that familiar exhilaration feeling (sensation-seeking effect) they get when behind the wheel (see Nordhoff *et al*., 2016; Ryder, 2019) and may even be more prone to car-sickness as a passenger, additional reasons for fearing that AV technology threatens their very quality of life. The expectation is that driving control would negatively affect AV adoption in both the private and shared forms, and would lead to individuals being unlikely to ever buy an AV.

A second latent construct, mobility control, captures emotive feelings related to a desire to be in control of mobility. This may involve the need for substantial freedom to choose the "when, where, and the with whom" of travel. The ability to have access to transportation immediately is paramount, with an emphasis on the ability to make spur-of-the-moment plans and to change existing plans. The flexibility in mobility implies little patience accommodating other individuals' schedules or desires, and a need for substantial independence in mobility decisions. Additionally, those who desire mobility control may be prone to linking more than one activity on a single sojourn. Thus, the expectation is that individuals with a high mobility control need will be more likely to own a private vehicle, whether a regular vehicle (RV) or an autonomous vehicle (AV). It is even possible that such individuals may place a slightly higher premium on an AV (relative to an RV), because they are even less tied down to chauffeuring children and older individuals to activities (Panagiotopoulos and Dimitrakopoulos, 2018). Of course, such individuals are likely to shun SAVs. The need for mobility control may make them rely more on regular vehicles in the early AV stages (because of the uncertainty of the resulting environment on their mobility needs at the initial stages), though they may eventually want to buy an AV after things settle down some.

The third latent construct, AV safety concern (or simply safety concern in the rest of this thesis), has been shown in earlier studies to influence AV interest/adoption. While many experts expect that AVs will eliminate the majority of human driving error, making roadways safer for pedestrians, bikers, and vehicle inhabitants (see, for example, Mueller *et al*., 2020), the public remains relatively wary regarding these claims. Evidence suggests that many individuals believe AVs will degrade traffic safety levels, because machines simply cannot be trusted to undertake the information processing that a human brain is capable of, especially in complicated traffic situations or edge cases (that is, situations that are challenging and highly improbable but not impossible). Individuals concerned with AV safety are particularly less accepting of AV use for picking up/dropping off children and travel in areas with substantial pedestrian traffic (see de Miguel *et al*., 2019; Moody *et al*., 2020; Nair and Bhat, 2020). The expectation is that a heightened safety concern would lead to individuals continuing to purchase an RV (rather than an AV or use SAV). Such individuals are very unlikely to ever buy an AV, particularly as "first-buyers".

The final latent construct, tech-savviness, represents an individual's familiarity of and affinity towards technology. Tech-savviness can influence AVD and DAD in two different pathways. The first is due to the ability to efficiently and productively use the travel time gained by not having to drive (Moore *et al*., 2020). Tech-savvy individuals are more inclined to use a smartphone (and information and communication technology or ICT devices more generally) and multi-task (Astroza *et al*., 2017). The second pathway corresponds to a simple and straightforward fascination to explore and be up-to-date on the world's latest technology (Kesharwani, 2020). Individuals who are tech-savvy can be expected to be more likely to purchase AVs. These individuals, knowing that initial technology "kinks" will be straightened out in due course, may decide to wait just a little longer before an AV purchase, rather than be the first-adopters.

Each of the above four latent constructs are not directly observed. However, the survey collected indicators of these variables, responses to each of which was elicited on the same five-point Likert scale of (1) Strongly disagree, (2) Somewhat disagree, (3) Neutral, (4) Somewhat agree, and (5) Strongly agree. A traditional confirmatory factor analysis of the indicators identified the most appropriate indicators for each latent construct. The complete descriptive statistics for each variable's indicators are provided in Appendix C.

The four latent constructs correspond to a total of 13 indicators (four for driving control, three for mobility control, four for safety concerns, and two for tech-savviness). The indicators for each latent construct are reduced to a single continuous "factor" using a traditional confirmatory analysis (see Moore *et al*., 2020 for a similar procedure). These continuous factors are then used as sample continuous dependent values that are manifestations of the latent constructs (see discussion in Appendix C).

3.2.3 Main Outcome Variables

As previously mentioned, there are two main outcomes, a rank-ordered nominal outcome related to the AVD choice, and an unordered nominal outcome associated with the DAD choice. The AVD ranked choice was obtained through two stated choice questions, while the DAD choice was a simple stated intention question.

Table 1 presents the stated ranked choice distribution for the AVD decision. The table cumulates the ranked choice responses across both the stated choice questions, leading to a total sample size of 2,042 responses (1,021 respondents × 2). Of course, our methodology (discussed in the next section) recognizes that the 2,042 responses are not independent, and that there is likely correlation across the two responses from each individual. The second column of Table 1 indicates that a regular vehicle (RV) is the most likely pick (45.9%) as the first-rank choice across the 2,042 choice occasions, with AVs also being picked as the first-rank in a sizeable percentage (40.9%) of the responses. Not surprisingly, and consistent with the high degree of agreement with the indicator "I definitely like the idea of owning my own car", a relatively small (though not insignificant) percentage of responses correspond to SAVs being the first ranked choice. With regard to the second ranked choice, it is interesting to note that, among those who pick RVs as the first-rank choice, there is a slightly higher proportion willing to consider SAVs relative to AVs in this second-rank compared to in the first rank (the percentage for SAVs in the second rank is 30.9% for those who pick RVs as the first ranked choice, while the corresponding figure for SAVs is 13.2/(13.2+40.9)=24.4% in the first rank). That is, conditional on keeping a regular vehicle, there is a higher likelihood of depending on SAVs than in an unconditional situation. However, the situation gets reversed if an AV is picked as the first ranked choice. In this case, the percentage choosing SAVs (rather than RVs) is 19% in the second rank, compared to 13.2/(13.2+45.9)=22% choosing SAVs in the first rank from among non-AV choosers. That is, conditional on purchasing an AV, it appears that individuals are even less likely to use an SAV than in an unconditional situation. Particularly interesting is also that, if an SAV is chosen in the first rank, it is much more likely that an AV is chosen in the second rank than in the unconditional first rank choice proportion of AV choosers from among non-SAV choosers. That is, if an SAV is decided on as the primary form of transportation, it is more likely to be supplemented by an AV than an RV. The last column of the table provides the percentages of the first and second ranked choice combinations, which also reflect the above discussion. Overall, the RV-AV and AV-RV combinations are most likely. In terms of SAV use, it is most likely to be used as a supplement to an RV.

Next, the cross tabulation of the two sets of main outcomes are presented in Table 2 with regard to the first-rank choice in the AVD dimension. Note that the response for the DAD question is at the individual-level (1,021 individuals), while the response for the AVD question from the stated choice experiment is at the choice occasion level (1,021×2=2,042) level. For compatibility, we have simply duplicated the DAD response to match up to the 2,042 choice occasions of the AVD responses. The final row of the table provides the univariate descriptive statistics for the DAD decision. As can be observed, a majority (68.4%) of the respondents indicate that they will eventually buy an AV (EB), with a very low percentage (4.8%) indicating that they will the first-to-buy (FB). More than a quarter of the respondents indicate that they will never buy an AV (NB). The cell values in the table provide both the actual number of responses in each cell as well as the column-wise percentage in parenthesis. The table clearly shows the linkage between the AVD and DAD choice decisions. For example, the NB respondents are substantially more likely to be those who choose an RV as their first ranked choice along the AVD dimension of choice. Similarly, the FB respondents (and to a lesser extent the EB respondents) are substantially more likely to be those who choose an AV as their first ranked choice.

A key issue to note here is that, in addition to the benefits of using a ranked choice preference mechanism for any unidimensional choice situation, as discussed earlier in Section 3.1, the use of a ranked elicitation mechanism also helps in multidimensional choice modeling. For instance, Table 2 shows only 11 responses associated with the SAV-FB combination, which can be inadequate when estimating a joint AVD-DAD model with this SAV-FB combination. However, Table 2 shows only the crosstabulation of DAD with the first-ranked AVD alternative. In addition to the 268 first-ranked SAV responses, we also have the 414 second-ranked SAV responses. These second-ranked responses, contribute to the enhanced ability to model the AVD and DAD dimensions jointly. For example, instead of only 11 observations in the SAV-FB combination if only the first-ranked SAV choice were used, we now have a total of 45 observations in this combination if both the first-ranked and second-ranked SAV choices are considered.

3.2.4 Framework for Jointly Modeling Continuous, Nominal, and Ranked Outcomes

In this study, we jointly model the four continuous outcomes (representing the four latent stochastic constructs of interest) and the two nominal outcomes (the AVD and DAD outcomes). Two instances of AVD choice are available from each respondent, corresponding to the two SP choice scenarios presented to each respondent. To accommodate the individual-level correlation among these two AVD choice instances, we model these two instances as two separate outcomes in our individual-level multivariate model. By doing so, we explicitly recognize the 'panel-like' correlation effects in the two AVD responses from each individual, as engendered by the effects of common individual-level stochastic latent constructs impacting alternative utilities at both choice occasions of the same individual. Thus, we jointly model three main outcomes (the two AVD ranked choice instances and the DAD first-choice), along with the four latent constructs, and allow error correlations among these seven endogenous variables. However, the two AVD choice instances reflect the same decision-making process, and a single set of parameter effects and correlations (with the latent constructs) are estimated across the two AVD ranked choice instances.

An important methodological contribution of this thesis is that we model a mix of continuous variables as well as a nominal variable (DAD) and a ranked variable (AVD). However, the mathematics of the model set-up, the identification conisderations, and the estimation procedure entail a good bit of notation and matrix manipulations. To conserve on space, as well as to focus on the empirical insights, we relegate the model set-up and the estimation procedure to Appendix D and Appendix E.

First-rank choice	Count	%	Second-rank Choice	Count	% Based on First-choice	% Based on Total
Regular Vehicle (RV)	938	45.9	Autonomous Vehicle (AV)	648	69.1	31.7
			Shared AV (SAV)	290	30.9	14.2
Autonomous Vehicle (AV)	836	40.9	Regular Vehicle (RV)	677	81.0	33.2
			Shared AV (SAV)	159	19.0	7.8
Shared AV (SAV)	268	13.2	Regular Vehicle (RV)	108	40.3	5.3
			Autonomous Vehicle (AV)	160	59.7	7.8
Total	2042	100.0				

Table 1. Ranking of Next Vehicle-Type Purchase

	Response Category (%)			
First-choice	I will never buy an AV (NB)	I will be one of the first people to buy an AV (FB)	I will eventually buy an AV, but only after these vehicles are in common use (EB)	*Total (%)*
Regular Vehicle (RV)	425 (77.7)	22 (22.5)	491 (35.1)	*938 (45.9)*
Autonomous Vehicle (AV)	62 (11.3)	65 (66.3)	709 (50.8)	*836 (40.9)*
Shared AV (SAV)	60 (11.0)	11 (11.2)	197 (14.1)	*268 (13.2)*
Total (%)	547 (26.8)	98 (4.8)	1397 (68.4)	2042

Table 2. Distribution of First Ranked Choice of Next Vehicle Purchase by Timing of AV Purchase

Chapter 4: Model Results[8]

The final model specification was developed through a systematic process of analyzing alternate combinations of explanatory variables, while removing statistically insignificant ones. Individual demographic and household characteristics, such as age, household size and household vehicle fleet size, were tested as dummy variables in the most disaggregate form possible, and progressively combined based on statistical tests to yield parsimonious specifications. Different functional forms were tested for the time and cost variables in the AVD model specification, including a linear form, a nonlinear form based on piece-wise linearity, and dummy variables for specific groupings of time and cost. The sensitivity to cost was also interacted with individual-level variables such as household income (to reflect the decreasing sensitivity to cost with income). However, the final specification turned out to be rather simple, including a simple linear form for both the fixed cost and variable cost of the different AVD alternative.

Interestingly, in our specification tests, the effect of waiting time for the SAV mode consistently came out to be statistically insignificant. This suggests that respondents may have actually grasped the concept of SAVs quite well. The introduction to the AV questions was quite descriptive of what an AV means and what an SAV means, with reference to SAVs being Uber and Lyft type services available today except without a driver. Because Uber and Lyft services can be scheduled in advance based on timing need, the concept of wait time is not likely to be that important as for traditional fixed-schedule transit services, which may be reflected in our results as the statistically insignificant effect of SAV wait time. Of course, an alternative explanation for our

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[8] 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. Conducted the writing, analysis, and modeling for this paper.

finding of the lack of effect of waiting time for the SAV mode is that SAV waiting time simply does not feature in a decision as important as medium-term mobility adoption decisions.

In the specification testing phase, the latent constructs themselves were introduced directly as well as interactions with individual-level variables and the time/cost variables (to capture variations in demographic effects as well as sensitivity to times/costs based on latent construct levels). Some of the interaction effects with demographics turned out to be important, but the interaction effects with time and cost were again consistently statistically insignificant.

As discussed earlier, our estimation proceeds by first identifying the most appropriate indicators for each of four latent constructs based on a confirmatory factor analysis, and then using the loadings of each latent constructs on the indicators to construct continuous values of the latent constructs for use in the model estimation. The loadings of the latent constructs on the construct indicators are not of primary interest in this thesis and are available in Appendix C. Suffice it to say that the loadings were significant and had the expected sign. The other results are discussed next, starting first with the SEM results relating the individual-level variables to the latent constructs, and then proceeding to the results for the main outcomes. However, all these parameters are estimated at once in a joint estimation, and are being presented in sequence simply for presentation ease.

One final note before proceeding to the discussion of results. In some cases, we have retained variables that were marginally statistically significant, because of their intuitive interpretations and important empirical implications. In this regard, the methodology used involves the estimation of a large number of parameters, so the statistical insignificance (at the 95% confidence level) of some coefficients may simply be a result of having only 1,021 respondents. Also, the effects from this analysis, even if not highly statistically significant, can inform specifications in future investigations with larger sample sizes.

4.1 LATENT CONSTRUCTS

The effects of socio-economic and household characteristics on the four latent constructs are presented in Table 3. Women appear to be more likely than men to want to be in control of their driving, are more concerned with safety, and are less tech-savvy. The first result, while may not be considered consistent with the usual stereotypical characterizations of societal expectations, has backing in the psychology and ethnography literatures. In fact, a study by Charness *et al*. (2018) also obtained a similar result with women less likely to relinquish driving control to AVs. The results here and in Charness *et al*. (2018) may be explained by the fact that general control in life should be distinguished from specific aspects of life control, such as driving control. Indeed, the usual asymmetric power balance in overall life patterns can result in women feeling a lower sense of general life control. Thus, women have an increased desire for a sense of empowerment relative to men, or at least are more reluctant to relinquish any sense of power that they already feel they have (Bulte and Lensink, 2019), which leads to a higher need to retain driving control. This is also supported by identity-based consumer behavior, based on which women associate driving with an expression of free-spiritedness, independence, and empowerment, thus alleviating feelings of vulnerability in an otherwise asymmetric power balance in life (Skuladottir and Halldorsdottir, 2008; Leung *et al*., 2018). Thus, both the asymmetric power dynamics in general life as well as self-identity considerations can explain the higher driver control among women relative to men. The second result in Table 3 associated with gender (related to women having heightened safety concerns) is well established in the literature (see, for example, Acheampong and Cugurullo, 2019). There are at least two possible explanations for this result. The first explanation is that women tend to be more risk-averse than men, because women experience feelings of nervousness and fear more so than men in anticipation of potentially negative outcomes (Meier-Pesti and Penz, 2008; Borghans *et al*., 2009). This result is also consistent with the Theory of Basic Human Values (Schwartz, 1992), which identifies that men generally attribute more value to new experiences, stimulation, self-direction and hedonism (Schwartz and Rubel, 2005; Vianello *et al*., 2013), making them more overconfident in uncertain situations. A second explanation is that women tend to be more responsible for managing household routines, including transporting children to extra-curricular activities (as aptly coined by the term "soccer-moms"). As a result, they are most comfortable driving by themselves when traveling with children rather than yielding that control to anyone else, let alone a machine (see Ciciolla and Luthar, 2019; this reason is particularly likely to be an important one, given one of the indicators for safety concern explicitly relates to picking up/dropping off children without adult supervision). The enhanced safety concern among women in the presence of children in the household, as represented by the interaction term "female*presence of children in the household" reinforces this second explanation. Finally, in terms of gender effects on the latent constructs, women tend to be less tech-savvy than men. This is different from the recent studies of Lavieri and Bhat (2019a) and Nair and Bhat (2020) that found no statistically significant difference between men and women in the level of tech-savviness, but is consistent with the gap between genders in access to technology in the digital age (Mushtaq and Riyaz, 2020). As discussed by Mustaq and Riyaz, women are typically the multi-taskers of the family, as they tend to household chores and are the household's primary caregivers, leaving minimal free time for women to learn, adapt and use new technologies.

Age impacts all the latent constructs. Those in the elderly group (64 years or older) ascribe a high premium to driving and mobility control, and are much more safety concerned and less tech-savvy than their younger peers. The need for driving control among the elderly may be traced back to a need to maintain a self-perception of being in control in general and raising mental self-esteem at a stage of life when their physical self-esteem may not be as high as during their yester years. Also, the advent of AVs could engender a disruptive change in the way of life for older individuals, especially because older individuals are typically less open to change and new experiences (Kessler, 2009; González Gutiérrez *et al*., 2005). These individuals have driven most of their life, and are naturally less trusting of disruptors such as AVs (see also Haboucha *et al*., 2017; Voinescu *et al*., 2020). Similar reasons can explain the need for mobility control among the elderly. While the elderly tend to have relatively small-sized social networks, and also travel less outside the home due to mobility constraints (see Paillard-Borg *et al*., 2009; Bhat *et al*., 2020), they tend to be much more zealous in preserving the spatio-temporal rigidity and schedule of their out-of-home activity participations (Nikitas *et al*., 2018). The heightened safety concern related to AVs may be traced back again to a distrust and skepticism in new technology, in part engendered by prior exposure to technologies that were initially hailed as positive “breakthroughs”, but turned out to have dangerous “side-effects.” Another reason provided by Nair and Bhat (2020) is that traditional TV and radio media, which constitute important sources of information on automated driving for older individuals, tend to focus more on AV risks (such as accidents) than benefits (as part of news sensationalism). This immediately gets on the radar of older individuals, who then question AV safety. Finally, in the context of age effects related to the latent constructs, the lower levels of tech-savviness among the elderly is a consistent finding. Younger individuals (millennials, for example) grew up in an era of ubiquitous internet and communications technology (ICT), while baby boomers had to adapt to technological changes in adulthood (Correa *et al*., 2010; Helsper and Eynon, 2010). Further, it takes a greater effort for older generations to use digital devices as proficiently as younger individuals (see Bolton *et al*., 2013; Berkowsky *et al*., 2017; Rogers and Mitzner, 2017). Also, the elderly tend to be more reticent in using new technology because of being risk-averse in general and also not being very adept with technology (Hamid and Cheng, 2013; Oliveira and Baldi, 2019; Schmid and Axhausen, 2019), further leading to a snowballing effect of their already low tech-savviness.

In addition to the age and gender effects, the results in Table 3 indicate that employed individuals are less concerned about safety-related problems due to AV use. Employed individuals are routinely subjected to long commute delays and are more likely to encounter traffic accidents during their travel in the current human-driven environment, presumably leading to a perception that machines can do better. These individuals also are submerged in a "sea" of technological advancements at their workplace, and thus may be less distrustful of AV technology (see Nair and Bhat, 2020). The results also show that individuals with an education beyond high school show a lower need for driving control, but display higher tech-savviness levels. The higher tech-savviness among the highly educated is not surprising, because a thorough grasp of ICT use is essential in today's increasingly knowledge networking-based instruction technology and economy (van Laar *et al*., 2017). Finally, in the context of latent constructs, high income individuals display a higher level of tech-savviness. This relationship between technology savviness and level of income is widely referenced in the socio-technical literature as well as the recent transportation literature (see Kalba, 2008; Lavieri *et al*., 2017; Nair and Bhat, 2020).

The estimated correlations between the error terms of the latent constructs (see bottom of Table 3) are as one would expect. Unobserved factors that increase the need for driving control also increase the need for mobility control, and both these control constructs are positively correlated with tech-savviness. Interestingly, individual-level unobserved factors that heighten safety concern also reduce the need for mobility control. Finally, individuals who are intrinsically tech-savvy are less concerned about safety issues. This latter result may be because tech-savviness is associated with a higher trust of technology and its reliability in the first place.

Variables (base category)	Structural Equations Model Component Results							
	Driving Control		Mobility Control		Safety Concern		Tech-Savviness	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Gender (male)								
Female	0.154	1.78	--		0.427	5.89	-0.215	-2.64
Female*presence of child(ren) in the household	--		--		0.180	1.40	--	
Age (younger than 64)								
64 or older	0.367	2.74	0.307	1.69	0.247	3.95	-0.501	-3.35
Employment Type (unemployed)								
Employed	--		--		-0.196	-3.39	--	
Education (completed high-school or less)								
Higher Education	-0.148	-1.90	--		--		0.155	1.99
Household Characteristics								
Income (<$100,000)								
≥$100,000	--		--		--		0.133	1.65

Correlation among Latent Constructs	Construct	Param.	t-stat	Param.	t-stat	Param.	t-stat	Param.	t-stat
	Driving Control	1.000	--	0.218	3.94	0.000	--	0.204	4.63
	Mobility Control			1.000	--	-0.198	-4.62	0.281	6.65
	Safety Concern					1.000	--	-0.232	-4.79
	Tech-Savviness							1.000	--

Table 3. Determinants of Latent Variables

4.2 Main Outcomes

Table 4 presents the coefficients estimated for the AVD and DAD outcomes. These coefficients refer to the impact on the underlying utilities characterizing the outcomes. The constants in the first row do not have any substantive interpretations, and simply are estimated to best match with the observed ranked choice proportions and choice proportions (conditional on the determinant variables). Any cells marked "--" in Table 4 indicate that the corresponding column alternative(s) serve as the base "category" in introducing the latent construct effects and the individual-level variable effects.

Latent construct effects: The direction of impacts of the latent constructs are mostly as expected and discussed earlier in Section 3.2.2, with a few minor variations. In particular, while individuals with a high need for driving control are less likely to buy an AV, driving control does not impact SAV use utility directly. This has the result of increasing SAV use through a probability cross-effect, perhaps because even these individuals see some value in SAV use for specific occasions such as after a social night out (Burtch *et al*., 2019). Additionally, our analysis revealed the presence of interactions of the two control-related latent constructs with gender and age. For the same level of driving control, women appear much less likely to purchase an AV relative to men, while younger individuals (below the age of 30 years) appear to be less tempered in their aversion toward AVs even as they hold a high desire to retain driving control. In other words, older individuals are more likely to translate their driving control desire into investing in a regular vehicle at the next purchase occasion. In the context of the interactions with mobility control, for a man and a woman with the same level of mobility control need, women appear to be more inclined to purchase an AV. This perhaps is a result of women being more time-poor than men (especially if they have children; see Bernardo *et al*., 2015), and so, for a given mobility control need, they may be more willing to adopt an AV as a means to use time productively in a hands-off environment and pursue social-recreational activities of their choice.

Effects of individual-level characteristics: The individual-level effects in Table 4 provide the direct effects of socio-demographics, beyond their indirect effects mediated through the latent constructs (the indirect effect of a socio-demographic variable is the product of the coefficient of the latent construct in Table 4 and the coefficient of the socio-demographic attribute for the latent construct in Table 3). Not surprisingly, after considering the indirect effects through the latent constructs, not many individual-level variables have a direct effect on the AVD or DAD choice decisions.

Age continues to have an important effect, even after considering its indirect effects through the latent constructs. That is, for two individuals (one being less than 65 years of age, and another being 65 years of age or older) with the same latent construct values, the older individual is more likely to spurn AV technology of any kind as well as never buy an AV. These are consistent findings in the AV adoption literature, suggesting added technology distrust and unwillingness to change current habits beyond that manifested through the latent constructs (see, for example, Voinescu *et al*., 2020). Beyond age, no other individual characteristic has a direct effect on the main outcomes, though a few characteristics associated with the household of the respondent do have a direct effect.

The effect of household income on technology adoption is well established in the literature. Wealthier individuals have the financial wherewithal to afford new technological devices and are usually the first to have access to expensive new technologies (see, for example, Lavieri *et al*., 2017; Liu and Yu, 2017). The second household variable, which influences only the AVD dimension of choice, is whether a household currently has a vehicle or not. Relative to households with no vehicles, individuals from households with one or more vehicles have a lower propensity to purchase AVs or use SAVs. That is, such individuals have a high propensity to purchase a regular vehicle, and are particularly averse to using SAVs. The higher propensity of non-zero vehicle households to purchase regular vehicles rather than use AVs in the future is consistent with the finding from Liljamo *et al.* (2018) that non-zero vehicle households have a significantly lower positive attitude to AVs. Additional investigation to better understand this effect would be fruitful, though it is possible that this is simply a manifestation of a "leapfrogging" mindset among individuals residing in current zero vehicle households.[9] The lower propensity to use SAVs among individuals in non-zero vehicle households is to be expected, since such individuals are less likely to have experienced ride-hailing as it exists today (see Dias *et al.*, 2017; Lavieri and Bhat, 2019a,b), and so may be less familiar with shared services and less comfortable with SAVs in the future.

<u>Vehicle/service attributes:</u> Two cost variables were considered in the AVD stated choice questions: a fixed per month cost (applicable only to the RV and AV option, and not to the SAV option), and a variable per mile cost (applicable to all options). As would be expected, the utility of the RV and AV options reduce as the fixed cost of these alternatives increases, and the utilities of all the three alternatives reduce as the variable cost increases. Assuming that an average vehicle mileage is 1000 miles a month (the average for the U.S. is closer to 1,125 miles per month or 13,500 miles per year), the

[9] The term "leapfrogging" is generally used to refer to a less industrialized nation "catching up" with more developed countries on a new technology, completely bypassing an intermediate development point (as happened with mobile phones where less developed countries skipped investing much in land-line communications infrastructure). Our use of the term here is more at an individual-level choice mindset, based on foregoing the purchase of a current technology product (regular vehicles) in anticipation of a new, better product in the near future (an AV).

effective coefficient on actual variable cost is (-0.161/1000). The corresponding coefficient on fixed cost is, of course, (-0.955/1000), given the fact that the model uses fixed cost in units of 1000s (so, for example, the monthly cost of $300 is used as 0.3 in estimation). Comparing the coefficients on fixed cost and the effective coefficient on variable cost, it is not surprising that, for the RV and AV alternatives, the sensitivity to fixed cost is higher than that on variable cost, which is understandable, since the fixed price constitutes a large investment at one point in time, while the variable cost is incurred over time (see Bhat *et al*., 2009). The compensatory variation between fixed and variable cost (again, at the driving mileage of 1000 miles per month) indicates that a dollar of fixed cost is considered equivalent to 16.9 cents [=(0.161/0.955)×100] of variable cost. Fixed costs do not apply to the SAV mode, but the actual variable costs for SAVs are higher than for RVs or AVs. According to our results, if only financial considerations were in play, for a vehicle mileage of 1000 miles per month, and at the average fixed cost and variable cost for RVs/AVs at $200 per month and 30 cents per mile, the SAV cost can be no more than 1.49 cents per mile [=(0.955×0.2 + 0.161×0.30)/(0.161)] for the SAV to stand some chance of being chosen. Of course, this is based purely on financial considerations, and the strong negative constant for SAVs suggests that SAV use is likely to be quite low, unless specific policy actions are taken to promote SAV use.

<u>Correlation across latent constructs and AVD/DAD alternatives:</u> The correlations across the latent constructs have already been discussed earlier in Section 4.1. Further, the correlations across the main outcomes themselves (as well as the correlation across the two responses from the same individual) are engendered in our framework through the effects of the individual-level stochastic latent constructs, as discussed earlier in Section 3.2. In addition, we also consider the latent constructs to be co-endogenous with

the main outcome variables.[10] In the latter context, three correlation terms turned out to be important. The first is a negative correlation between the safety latent construct and the AV alternative of the AVD dimension (correlation of -0.180 with a t-statistic of -4.78). As discussed in Section 2.1, when this correlation term was ignored in our estimation, it exaggerated the positive effect of safety concern on RV purchase (that is, equivalently, it exaggerated the implied negative effect of safety concern on the AV alternative). A second positive correlation was obtained between the mobility control latent construct and the first-buy (FB) alternative of the DAD dimension (0.184 with a t-statistic of 1.90). When this correlation was ignored, it turned up as a "spurious" positive effect of the mobility control latent construct on the FB utility. The third correlation term was a positive association between tech-savviness and the FB alternative, due to unobserved factors (0.177, with a t-statistic of 1.82). For example, it is possible that a child raised to be intensely curious would try, as an adult, to "jump off the block" to be the first to explore new adventures and products. Such an individual may also be tech-savvy simply because of her/his curiosity. If this generic "curiosity" effect is ignored, it would exaggerate how much the adoption of AVs could be encouraged based on campaigns to promote tech-savviness. Indeed, as can be seen from Table 4, the tech-savviness latent construct does not even show up as a determinant of the FB alternative when we considered this correlation between tech-savviness and FB; however, when the error correlation effect was ignored, a "spurious" positive tech-savviness latent construct effect on the FB alternative was the result.

[10] To be precise, we can only estimate the correlation of the latent constructs with the differenced error terms in the AVD and DAD dimensions. But, for ease in interpretation, we assume that there is no correlation among (a) the latent constructs and the RV alternative in the AVD dimension, and (b) the latent constructs and the NB alternative in the DAD dimension. Again, this is innocuous, and is only done for ease in interpretation.

Exogenous Variables (base category)	AV adoption (AVD) dimension: *"What will you buy?"*						Duration of AV adoption (DAD): *"When will you buy an AV?"*			
	Regular Vehicle (RV) (Base)		**Autonomous Vehicle (AV)**		**Shared Autonomous Vehicles (SAV)**		**First to purchase (FB) (Base: Never purchase an AV)**		**Eventually Purchase (EB) (Base: Never purchase an AV)**	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Constant	--		0.078	1.47	-0.666	-6.92	-1.164	-8.97	0.715	12.43
Endogenous Effects										
Latent Variables										
Driving Control	--		-0.246	-4.86	--		-0.870	-6.67	-1.406	-14.63
Mobility Control	--		0.061	1.54	-0.547	-14.74	--		0.246	3.36
Safety Concern	0.144	4.20	--		--		-0.754	-6.04	-0.132	-1.75
Tech-Savviness	--		0.064	1.75	--		--		0.100	1.68
Latent Variables Interactions										
Driving Control*Female	--		-0.118	-2.04	--		--		--	
Driving Control*Age<30	--		0.098	1.69	--		--		0.130	1.62
Mobility Control *Female	--		0.199	3.03	--		--		--	
Individual-level Characteristics										
Age (below 64 years)										
64 or older	--		-0.277	-2.58	-0.165	-1.73	-0.252	-1.76	-0.252	-1.76
Income (<$100,000)										
≥$100,000	--		--		--		0.533	3.79	--	
Vehicles per Household (no vehicles)										
At least one vehicle present	--		-0.100	-1.61	-0.201	-3.23	--		--	
Vehicle/service attributes										
Fixed cost per month (in 1000's of $)	-0.955	-6.08	-0.955	-6.08	NA		NA		NA	
Variable cost (in $ per mile)	-0.161	-4.72	-0.161	-4.72	-0.161	-4.72	NA		NA	

Table 4: Results of AVD and DAD Joint Model

4.3 MODEL GOODNESS OF FIT

The performance of the joint model may be compared with that of a restricted model (that is, an independent model) that does not consider latent constructs (and consequently also ignores any type of dependency between the outcomes). That is, we evaluate a predictive log-likelihood value purely for the AVD and DAD dimensions, using the convergent parameter values from our joint estimation (focusing on the first-choice for the AVD dimension). Next, we estimate an independent model for the AVD and DAD dimensions, without consideration of any latent variables. In this independent model, to put things in as equal a footing as possible in terms of observed variable effects, we include the determinants of the latent constructs as explanatory variables. We next compute a predictive log-likelihood for this independent model focusing again on the first-choice for the AVD component. We also compute the log-likelihood with only the constants in the AVD (for first-choice) and DAD dimensions.

Our joint model and the independent model may be compared using a predictive Bayesian Information Criterion (BIC) statistic [= $-\mathcal{L}(\hat{\theta})+$ 0.5(# of model parameters) log(sample size)] ($\mathcal{L}(\hat{\theta})$ is the predictive log-likelihood at convergence). The model with a lower BIC statistic is the preferred model. In addition to the comparison using the BIC value, an informal predictive non-nested likelihood ratio test may be used to compare the models. The adjusted likelihood ratio index of each model of the joint and independent models is first computed with respect to the log-likelihood with only the constants in the AVD and DAD dimensions:

$$\bar{\rho}^2 = 1 - \frac{L(\boldsymbol{\theta}) - M}{L(c)} \tag{1}$$

where $L(\boldsymbol{\theta})$ and $L(c)$ are the predictive log-likelihood functions at convergence and at constants, respectively, and M is the number of parameters (excluding the constants) estimated in the model. If the difference in the indices is $(\bar{\rho}_2^2 - \bar{\rho}_1^2) = \tau$, then the probability that this difference could have occurred by chance is no larger than $\Phi\{-[-2\tau L(c) + (M_2 - M_1)]^{0.5}\}$, with a small value for the probability of chance occurrence suggesting that the difference is statistically significant and the model with the higher value for the adjusted likelihood ratio index is preferred.

We also evaluate the data fit of the two models intuitively and informally at both the disaggregate and aggregate levels. To do so, we compute marginal multivariate predictions for the AVD first-choice and DAD dimensions jointly (for a total of nine combinations). At the disaggregate level, for the joint model, we estimate the probability of the observed multivariate outcome (AVD first-choice and DAD combination). Then, we compute an average (across individuals) probability of correct prediction at this two-variate level. Similar disaggregate measures are computed for the independent model. At the aggregate level, we design a heuristic diagnostic check of model fit by computing the predicted aggregate share of individuals for combinations of the two dimensions (focusing again on the AVD first-choice). The predicted shares for each of these nine multivariate outcomes is computed for all the two models and compared to the actual shares, and the absolute percentage error (APE) statistic is computed.

The results of the disaggregate data fit evaluation are provided in Table 5. The BIC values in the table clearly favor the joint model over the independent model. The predictive adjusted likelihood ratio indices, and the corresponding informal non-nested likelihood ratio statistics are also presented in the table. The probability that the adjusted likelihood ratio index difference between the joint model and the RES model could have occurred by chance is literally zero (see the penultimate row of the table), and the average probability of correct prediction from the joint model is better than that from the independent model.

Summary Statistics	Model	
	Joint Model	**Indep. Model**
Predictive log-likelihood at convergence	-2593.340	-2731.104
Number of parameters	47	25
Bayesian Information Criterion (BIC)	2756.160	2817.711
Constants-only predictive log-likelihood	-2841.526	
Predictive adjusted likelihood ratio index	0.0708	0.0301
Informal non-nested adjusted likelihood ratio test: Joint model versus Indep. Model	Φ [-15.915] << 0.001	
Average probability of correct prediction	0.1303	0.0902

Table 5. Disaggregate Data Fit Measures

At the aggregate level, the nine combinations of the main outcomes are identified in Table 6. For each of these combinations, the shares predicted by the joint model are generally better than the independent model. Overall, across all the combinations, the weighted average (weighted by the share of each combination) of the absolute percentage error is 11.64% for the joint model, compared to 32.32% for the independent model (see the last row of Table 6). The aggregate fit measures in Table 6 reinforce the disaggregate level results in Table 5.

Alternative		Observed Share (%)	Joint Model		Indep. Model	
AVD	**DAD**		**Predicted Share**	**APE***	**Predicted Share**	**APE***
Regular Vehicle (RV)	Never Buy (NB)	20.813	17.411	16.346	12.421	40.321
	First Buy (FB)	1.077	1.339	24.327	2.120	96.843
	Eventually Buy (EB)	24.045	27.602	14.793	31.247	29.952
Autonomous Vehicle (AV)	Never Buy (NB)	3.036	4.499	48.188	10.404	242.688
	First Buy (FB)	3.183	2.736	14.043	2.055	35.438
	Eventually Buy (EB)	34.721	33.491	3.543	28.367	18.300
Shared AV (SAV)	Never Buy (NB)	2.938	3.327	13.240	3.368	14.636
	First Buy (FB)	0.539	0.689	27.829	0.654	21.336
	Eventually Buy (EB)	9.648	8.906	7.691	9.364	2.944
Weighted average across all combinations (%)				**11.64**		**32.32**

*APE: Absolute Percentage Error

Table 6. Aggregate Data Fit Measures

Chapter 5: Implications[11]

The estimation results in the previous section provide insights into direct and overall indirect effects of the individual-level characteristics on the two main outcomes of interest (AVD and DAD). However, for policy analysis purposes, it is more useful to partition the influence (on the main outcomes) of each individual-level characteristic into

[11] 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. Conducted the writing, analysis, and modeling for this paper.

the following five sub-effects: driving control effect, mobility control effect, safety concern effect, tech-savviness effect and the remaining direct effect. This analysis can be undertaken using the Average Treatment Effect (ATE effect; see Angrist and Imbens, 1991 and Heckman and Vytlacil, 2000), a method that calculates the impact on a downstream posterior variable of interest due to a treatment that alters the state of an antecedent variable from *A* to *B*. For example, if the intent is to estimate the "treatment" effect of age on AVD choice, *A* can be the state where an individual is 64 years of age or below, and *B* can be the state where the individual is 65 years or above. The impact of this change in state is measured in terms of the change in the shares of the outcomes 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 an individual-level variable impacts the main outcomes through mediating latent constructs, one can use the estimates from Tables 3 and 4 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 fixed cost and the variable cost variables. For the fixed AV cost, the base case corresponds to the current situation. The average fixed cost across individuals in this base case is $399. The "treatment level" for AV fixed costs corresponds to a decrease (for each individual in the sample) by $50 per month (about a 15% decrease over the average of $330 per month as estimated by the U.S. Bureau of Labor Statistics; U.S. BLS, 2018). The average fixed AV cost across individuals in this "treatment" case is $289. For variable costs, for the base level, we retain the current AV level presented to individuals in the choice experiment (the average across individuals of this AV variable cost is about 50 cents per mile), and consider an SAV cost of $1.75 per mile (this estimate is slightly more than current Uber ride-hailing costs of $1.65 per mile, based on Childress *et al*., 2015). The average difference between

SAV variable cost and AV variable cost in the base scenario is $1.25. For the treatment scenario, we decrease the SAV variable cost to $1.25 per mile; the average difference between SAV variable cost and AV variable cost in this treatment scenario is $0.75.

To compute the relative magnitudes of the contribution of each individual-level variable 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 in Tables 7 and 8. For completeness, we also provide the overall effect of each variable, which would be the sum of the individual sub-effects (after considering the directionality of effect).

The ATE effects in Table 7 (for the AVD dimension) and Table 8 (for the DAD dimension) enable us to extract important insights for policy actions. The ATE values (in the last column of the tables) are to be interpreted as follows. Consider the ATE effect of gender on the "AV" alternative for the AVD dimension. The last column of the first numeric row corresponding to this variable shows a value of -0.057. This implies that if 100 men were replaced by 100 women, about six (5.7 in the table) fewer individuals (of the 100) would choose an AV at the next purchase occasion. Other ATE values may similarly be interpreted. 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 AV shares. Thus, the sub-effects are labeled as "driving control decrease", "mobility control increase", "safety concern decrease", and "tech-savviness increase". The "% contribution by mediation through..." columns are then to be interpreted as follows. The value of 32% in the column for "driving control decrease" for the gender variable indicates that, in terms of magnitude, 32% of the sum of the contributions of each sub-effect (ignoring directionality) to the ATE change in AV purchase is due to the driving control sub-effect. The negative sign on 32% reflects the fact that the change from the base male category to the "treatment" female category would lead to a reduction in the "driving control decrease" effect (that is, this change leads to a decrease in AV purchase because women actually have a higher driving control need). On the other hand, this gender "treatment" leads to an increase in AV purchase share due to the mobility control increase sub-effect. The +5% entry for this sub-effect suggests that the mobility control sub-effect contributes 5% to the ATE change, and the positive sign shows that the sub-effect leads to an increase in the ATE effect. Other entries may be similarly interpreted.

The reader will note that there is not necessarily a correspondence in the magnitude or even sign of some coefficients from Table 4 with those in Table 7. This is because the coefficients in Table 4 refer to effects on utilities, while those in Table 7 correspond to share shifts in alternatives (based on probability shifts at the individual-level). For example, driving control has no impact on SAV utility in Table 4. However, the negative coefficient of driving control on AV purchase utility in Table 4 immediately implies that an increase in driving control need increases the probability of SAV use, which is the reason, for example, for the positive driving control effect of the gender variable for SAV use in the lower panel of Table 7.

5.1 AV ADOPTION (AVD) DIMENSION

The first row panel of Table 7 provides the ATE effects with respect to AV purchase, while the second row panel provides the corresponding effects for SAV use. For both the AV and SAV alternatives, in terms of individual-level characteristics, gender and age (particularly the latter) have, by far, the highest overall ATE impact (see the last column of the table).

Women are clearly much less likely to purchase AVs and use SAVs relative to men, based on the overall ATE effects. This is a result obtained in many earlier studies.

However, we are able to further partition this overall effect into attitudinal pathways of effect. Not surprisingly, safety concerns dominate the reason why women are more reluctant to jump onto the AV bandwagon (this safety concern effect is 51% of the total gender effect for the AV alternative and rises to 76% of the total gender effect for SAV use). Making women more aware of AV technology and its expected safety benefits may be a particularly effective strategy to increase AV and SAV uptake among women. Such AV information campaigns can be specifically targeted toward social groups that are typically dominated by women (such as religious and spiritual groups, and performance and arts groups), and at work places/professional groups associated with women-dominant professions (such as K-12 teachers, health information technicians, and public relations managers). Parent groups and parent-teacher associations (PTAs) may be another avenue to highlight potential AV safety benefits, and also address important and valid concerns about child transport, which, as Lee and Mirman (2018) find, is one of the leading reasons why women are less likely to be receptive to AVs. Specifically, issues related to whether or not young children needing restraint systems would be buckled up appropriately, and anxiety about the ability of AVs to navigate environments with aggressive drivers are important considerations. The design of AVs so that video and audio feedback to mothers (and parents in general) at the beginning and end of trips (for example, to assure parents that a child has been buckled up securely), may be a design feature that can alleviate safety concerns among women and mothers. Such designs may also contribute to reducing the driving control need for women and mothers, and thus increase AV purchase likelihood. Additionally, underscoring the benefits of gaining time for leisure/relaxation in an AV environment may help women be more willing to relinquish driving control. More broadly, working toward an egalitarian society, one in which there is gender symmetry in power dynamics across the professional, political, and domestic spectrums of life, would perhaps be a fundamental approach to address the issue of driving control among women.

Age has a much stronger overall effect relative to gender. In the context of age, there is clearly a high generic disinclination to purchase an AV among older adults, as reflected by the 61% sub-effect attributable to a direct effect. While additional investigation to explain this large age effect would be fruitful, it is quite likely that this direct effect is strongly correlated with the perceived usability and friendliness of the human-machine interface (HMI) as embedded in AVs. This issue is distinct from the concept of tech-savviness that is included in our current study. In particular, while an older person may be as tech-savvy in general as a younger individual, the older individual may perceive lower AV usability due to reduced cognitive ability, especially in potentially time-critical circumstances such as when traveling in a vehicle. In this regard, the gerontology and psychology literature has established that ageing is generally associated with a decline in cognitive ability (such as memory, attention, and verbal and visual/spatial information retention; see Deary *et al*., 2009 and Boot *et al*., 2013). This leads to getting more easily overwhelmed with information as one ages (Pearce, 2008), and suggests the need for careful HMI design for AVs if older individuals are to be brought into the AV fold. Such design features may include (a) providing voice functionality for most tasks, and multi-modal audio/visual interfaces for high priority human-to-machine instructions, (b) avoiding unintentional activation and de-activation of computer-human control exchange, (c) reducing clutter and using simple displays with large screens and buttons, and (d) a layered and streamlined interface using size, color, and contrast features. Of particular importance is avoiding clutter, because this can be off-putting for older individuals, given their reduced working memory and cognitive ability. In addition to AV design, video game interventions may be considered to improve the perceptual and cognitive abilities of the elderly, as has been examined by Basak *et al*., 2008, Nouchi *et al*., 2012, and Boot *et al*., 2013. These studies suggest that exposure to one specific task in a video game can transfer to a general improvement in cognitive ability across a broad range of even unrelated novel tasks. Older adults, in particular, appear to respond well to video games that involve some intellectual challenge, as opposed to fast-paced action games that tend to work better to improve cognitive ability among younger adults.

In addition to the direct age effect, the results also suggest that AV purchase among the elderly may be promoted by addressing their need for driving control and safety concern, as well as through tech-savviness information campaigns. Of these, addressing the driving control issue seems particularly important. As discussed earlier, retaining driving control may constitute a means for older adults to preserve a sense of identity and not disrupt their usual way of life. However, the new cohort of the elderly tend to be more physically active, and more open to "seeing the world" (Levy, 2020). This tendency can be beneficially tapped into by positioning AVs as the new "vehicle" for older adults to fulfill their bucket-list of places to visit, thus reigniting their sense of adventure and exploration. Doing so can also address any mobility control concerns that older adults may have with AV use. Addressing these mobility control concerns appear particularly important for SAV use among older adults, as reflected in the 41% contribution of this latent construct to the overall ATE for SAV use (see the row corresponding to age in the lower panel of Table 7). Promoting SAV use as a way to avoid the "hassle" of finding parking spots close to destination points can be a particularly effective way to highlight the positive benefits of SAV use and instill a sense of mobility control. Another approach can be to have a high priority SAV pre-reservation system for older adults, whereby they are guaranteed mobility services at times of their choosing during the week. This should alleviate any concerns among older adults about time delays caused by SAVs, while the typical spatio-temporal rigidity of the schedules of older adults should make such an arrangement practical for SAV fleet managers.

The overall ATE effects of employment status, education, and household income on AV and SAV use are relatively modest. While the employment status effect corresponds to a safety concern sub-effect, the education effect is primarily manifested through a driving control sub-effect, and the income effect is associated with a tech-savviness effect. Approaches to address the elevated safety concerns among those who are unemployed can be similar to those identified earlier for women. In the context of the education effect, similar to women, those who are not highly educated may view driving as one of the few ways to retain a sense of control and empowerment in their lives. In fact, some of these relatively low educated individuals make their living through driving for taxicab and ride-hailing companies (a study by the UCLA Labor Center (2018) observes that two-thirds of ride-hailing drivers depend on driving as their main source of income, and a high percentage of full-time ride-hailing drivers are recent immigrants with a low wage occupation). These individuals are likely to view driving automation as an act of robbing them of their very livelihoods. Thus, it is imperative that, even as AV adoption is promoted, affordable retraining programs are designed for those who will be directly impacted by automation.

Interestingly, our results show that interventions aimed at increasing tech-savviness considerations are generally less important than interventions aimed at decreasing driving control/mobility control needs and safety concerns. However, while campaigns to enhance tech-savviness levels (especially directed toward women, older adults, and individuals with low education levels and low income) may not yield substantial benefits, they can be used as supplemental strategies to increase AV uptake.

As observed by Nair and Bhat (2020) such tech-savviness campaigns should not be generic discourses about technology, but should emphasize AV technology and use in the context of the current lifestyles and habits of the target audience. Such campaigns should underscore the socio-technical element in technology adoption by integrating the technological "geek" with human social and anthropological considerations.

The trip-level attribute effects indicate, as expected, the relatively high sensitivity of individuals to the fixed cost of an AV and the variable cost for SAV. In terms of relative magnitude effects, a change in fixed cost by $50 per month has a higher impact on AV purchase than the employment status, education, and income effects. However, the age and gender effects still dominate. Similarly, a change in variable SAV cost from $1.75 per month to $1.25 per month has a reasonable impact on SAV use (see last row of Table 7), but is overshadowed (again) by the age effect.

5.2 Duration to Adoption (DAD) Dimension

The results for the DAD dimension indicate the strong effects of gender and income levels for the first-to-buy (FB) an AV alternative, while age and education dominate as the main determinants of the eventually buy (EB) alternative. Specifically, men and those with high incomes are the most likely first-buyers, while those who are older are the least likely to ever buy an AV; those with a high education tend to position themselves as AV purchasers in the post-first buy period. Clearly, if the goal is to accelerate AV uptake as soon as it is introduced, information campaigns directed at men and high income individuals would be most effective. By way of attempting to convince more women and old adults to become first-buyers or to become eventual buyers, especially if the hypothesis that safety will be substantially enhanced with the move toward AVs is proven over time, once again campaigns extolling the AV safety benefits and the advantages accruing from relinquishing driving control would generally be much more effective than campaigns to increase tech-savviness levels. Thus, the policy measures mentioned earlier (for promoting AV adoption and SAV use in the AVD dimension) in the group of women and older adults should also help decrease the time to AV adoption. At the same time, it would behoove automotive manufacturers to maintain a sustained information campaign directed toward the well-educated, as this should have good payoffs even if not immediately after the introduction of AVs in the market.

Variable	Base Level	Treatment Level	% Contribution by mediation through				% Direct Effect	Overall ATE
			Driving Control decrease	Mobility Control increase	Safety Concern decrease	Tech-Savviness increase		
Next vehicle purchase is an AV (Base: Buy regular vehicle)								
Socio-demographic								
Gender	Male	Female	-32	5	-51	-12	0	-0.0570
Age	<30	≥ 64	-20	4	-8	-7	-61	-0.2191
Employment Status	Unemployed	Employed	0	0	100	0	0	0.0012
Education	High school or less	Higher than high school	79	0	0	21	0	0.0188
Income	<$100,000	≥$100,000	0	0	0	100	0	0.0011
Cost effects								
Fixed cost for AV	Current cost	Decrease by $50						0.0381
Variable cost for SAV	$1.75	$1.25	-	-	-	-	-	-0.0120
No vehicle purchase and rely on SAV (Base: Buy regular vehicle)								
Socio-demographic								
Gender	Male	Female	12	-2	-76	10	0	-0.0012
Age	<30	≥ 64	7	-41	-9	2	-41	-0.0851
Employment Status	Unemployed	Employed	0	0	100	0	0	0.0033
Education	High school or less	Higher than high school	-70	0	0	-30	0	-0.0061
Income	<$100,000	≥$100,000	0	0	0	-100	0	-0.0002
Cost effects								
Fixed cost for AV	Current cost	Decrease by $50						-0.0108
Variable cost for SAV	$1.75	$1.25						0.0241

Table 7: Sociodemographic ATE effects for the AVD dimensions

Variable	Base Level	Treatment Level	% Contribution by mediation through				% Direct Effect	Overall ATE
			Driving Control decrease	Mobility Control increase	Safety Concern decrease	Tech-Savviness increase		
First to purchase an AV (Base: Never purchase an AV)								
Socio-demographic								
Gender	Male	Female	-29	0	-69	2	0	-0.0742
Age	<30	≥ 64	-40	-3	-24	1	-32	-0.0159
Employment Status	Unemployed	Employed	0	0	100	0	0	0.0192
Education	High school or less	Higher than high school	94	0	0	-6	0	0.0014
Income	<$100,000	≥$100,000	0	0	0	-9	91	0.0428
Eventually purchase an AV (Base: Never purchase an AV)								
Socio-demographic								
Gender	Male	Female	-71	0	-21	-8	0	-0.0202
Age	<30	≥ 64	-56	8	-4	-5	-27	-0.1151
Employment Status	Unemployed	Employed	0	0	100	0	0	0.0009
Education	High school or less	Higher than high school	93	0	0	7	0	0.0741
Income	<$100,000	≥$100,000	0	0	0	60	-40	0.0042

Table 8: Sociodemographic ATE effects for the DAD dimension

Chapter 6: Discussion and Conclusion[12]

AV technology adoption and the speed of adoption is shaped by many factors, including individual-level demographic characteristics, individual-level psycho-social attributes, and AV vehicle/SAV service characteristics. In this thesis, we examine this individual-level process, considering the psycho-social factors of driving control, mobility control, safety concerns, and tech-savviness. Including such factors helps go beyond passively witnessing the evolution of AV adoption trends to more proactively shaping the adoption pathway. In particular, by estimating the relative magnitudes of the psycho-social factors through which demographics influence AV adoption, we are able to design effective policy instruments and information campaigns that appeal to the specific psycho-social sensitivities of distinct population groups.

In this thesis, we have examined both the vehicle purchase decision (regular vehicle, AV, or not buy a vehicle and use SAV) in the specific time context of the next vehicle purchase (the AVD decision), as well as the duration to AV adoption (the DAD decision). The AVD choice is modeled using an SP choice design, while the DAD decision is based on the response to a stated intention question. An important departure from traditional SP choice design in our AVD modeling is that we use a ranking preference elicitation approach, rather than the typically used first-choice preference elicitation approach. This allows us to extract much more information than can be obtained in a first-choice analysis approach, as well as aids in joint multivariate modeling. The data used for the analysis is drawn from a 2019 Austin area survey of emerging mobility services.

An important element of the analysis is the introduction of two control-related psychological constructs; driving control and mobility control; that have received limited to no attention in the AV adoption literature. The inclusion of these two constructs was based on the notion that, from the point of view of individuals who value the driving/mobility experience,

[12] 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. Conducted the writing, analysis, and modeling for this paper.

automation can be perceived as an alienating development. Our model results underscore the importance of considering the two emotive control factors. More generally, the use of psycho-social factors as mediators of individual-level socio-demographics also allows a parsimonious approach to estimate the joint model of AVD and DAD.

The effects of individual socio-demographics reveal the strong influence of gender and age on AV adoption and SAV use in the AVD dimension, especially the age effect. The gender effect is manifested in both the AVD and DAD dimensions primarily through concerns about AV safety and losing driving control. Underscoring the expected safety benefits of AVs and also addressing concerns about child transport would be, by far, the most effective strategies to increase AV and SAV uptake among women, much more so than, for example, tech-savviness campaigns. The DAD results also suggest that the sub-population of men and/or individuals from high income households may be more embracing of AVs as first-buyers. The age effect gets manifested through the latent constructs, but also has a strong direct effect on the AVD and DAD decisions, with older individuals (age ≥64 years) more likely to spurn AV technology of any kind as well as never buy an AV. This result reinforces the notion from earlier studies, suggesting a combination of general technology distrust, an unwillingness to change current habits, as well as cognitive ability declines associated with aging as deterrents to AV technology acceptance. Potential countermeasures include careful AV HMI design that recognizes the cognitive and working memory limitations of older adults, video game interventions to improve perceptual and cognitive abilities, and addressing older adults' need for driving control. Interestingly, while it may be objectively true that AVs would hold the most benefit for older adults who cannot drive safely, driving control appears to provide a sense of identity and a reaffirmation of older adults' motor skills. Countermeasures aimed at highlighting the safety benefits of AVs, therefore, may not play out as intended when directed toward older adults.

The ATE effects of employment status, education, and household income on AV and SAV use are relatively modest in the overall. Our results also suggest that reductions in AV fixed cost and SAV variable cost can lead to AV and SAV uptake. In terms of AV fixed cost, a decrease of $50 per month can lead to seven additional individuals out of 100 choosing the AV alternative. In terms of SAV variable cost, a decrease from $1.75 to $1.25 cents can lead to about 3 additional individuals out of 100 choosing the SAV alternative.

The speed of adoption of AV technology, even after its full-scale introduction in the market place, is likely to be rather slow because cars have a rather long lifespan and are quite expensive to acquire. Our results suggest that the first-buyers in the market will be men and high income individuals. To target these first-buyers, campaigns illustrating the general allure of investing in flashy new capabilities and luxurious features of AVs would be most effective. Also, to increase the speed of uptake among women and older adults, campaigns highlighting safety benefits and the additional time to pursue other activities through relinquishing driving control would generally be much more effective than campaigns to increase tech-savviness levels.

Overall, our results emphasize the need to understand the effects of technology through a psycho-social lens. Technology developments and design cannot be divorced from careful investigations of habits and consumption motivations of different groups of individuals. Innovations that are viewed as encroaching on "my motor skill territory", and as reducing the sensation-seeking that accompanies driving (see Nordhoff *et al*., 2016), can lead to substantial resistance to adoption. Thus, careful and balanced messaging, customized to the audience, is critical in information campaigns to promote AV adoption. From a methodological perspective, the study highlights the value of using ranked choice questions in stated preference surveys.

There are many directions for future research. The magnitude of the direct age effect is quite high in our results, suggesting a need to further investigate the reasons for older adults' reluctance toward AVs. While a number of reasons for this large direct effect (beyond the mediating effects through the latent constructs) have been provided, there are still many unknowns. Also, while we do introduce a time frame element to the AVD choice decision (by anchoring the choice to the next purchase occasion), this could itself influence the AVD choice expressed (independent of objective feelings about AVs in general). For example, individuals who just purchased a regular vehicle a month before (essentially, a situation where the next purchase occasion may be years away) may be more likely to respond that they would purchase an AV at the next purchase occasion, while individuals whose last car purchase occasion was 10 years ago may be more likely to respond that they would purchase a regular vehicle at the next purchase occasion (simply because the actual benefits of AVs and the technology reliability of AVs would be less known in the immediate future than over a longer period of time). There are clearly pros and cons of tying the AVD choice decision to the next purchase occasion, an issue that would be interesting to study in the future. Future studies can also be supplemented with a finer resolution instrument to capture the AV purchase duration time frame, beyond the rather coarse grouping adopted in this study to characterize the DAD decision. Another related important direction is to strive toward introducing more realism in the response elicitation mechanism. As indicated by Zmud *et al*. (2016), AVs continue to remain abstract, thus conjuring up different images for different people and making such vehicles psychologically distant. In this uncertain and speculative context, the ecological validity of any analysis based on stated preference responses can be limited. A multi-modal approach to eliciting responses and intentions is needed, including virtual reality experiments of the type undertaken by Voinescu *et al*. (2020). In any event, there is a need to continually investigate the socio-technical considerations associated with AV adoption, as people become increasingly familiar with the technology and there is more clarity on the design features of an AV.

Appendix A: Stated Choice Question Set

Experimental Design Attribute and Levels					
Regular Vehicles (RV)		***Autonomous Vehicle (AV)***		***SAV***	
Fixed cost per month	**Variable travel cost per mile**	**Fixed cost per month**	**Variable travel cost per mile**	**Variable travel cost per mile**	**Waiting time**
\$200 \$300 \$500	\$0.25 \$0.50 \$0.75	\$150 \$200 \$225 \$250 \$300 \$375 \$500 \$625	\$0.25 \$0.50 \$0.75	\$1.50 \$2.25 \$3.00	3 minutes 6 minutes 9 minutes

Scenario Example		
Suppose AVs are now available for purchase, lease/rent, or to use via automated ride-hailing services, and half of the vehicles on the streets are AVs. What would you do when faced with your next car purchase decision in each of the following scenarios? Please rank the alternatives based on your preference (1=most preferred; 3=least preferred). Please do not give the same rank to multiple alternatives.		
Option A	***Option B***	***Option C***
Buy a regular vehicle	Buy an AV	Don't buy a vehicle and use AV ride-hailing/rental services
\$200/month + \$0.50/mile	\$350/month + \$0.50/mile	\$0/month + \$2.25/mile
Average wait time: 0 minutes	Average wait time: 0 minutes	Average wait time: 6 minutes

Stated Choice Experimental Design

Appendix B: Individual-level Sample Demographic Characteristics

The sample descriptive statistics of the individual-level characteristics are presented in Table 2 (see left panel), and compared, whenever possible, with the census population of the Austin-Round Rock, TX Metro Area, as estimated by the U.S. Census Bureau (2018). The table indicates a clear over-representation of women in our sample, relative to the 50-50 split as reflected in the Census data for the Austin-Round Rock region. Not surprisingly, given our social media-based recruitment efforts and University-based efforts, the sample is skewed toward younger individuals (58.4% 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). The Census does not report the number of students in the region, which makes it rather difficult to compare employment rates between our sample and that from the Census, especially given that a number of students both characterize themselves as being a student as well as being employed. In terms of education levels, again, our sample shows a markedly lower percentage of individuals who have completed high school or less (13.7% compared to 29.0% from the Census) and a higher percentage of individuals who have completed some college or technical school (35.4% relative to 25.0% from the Census). However, the distributions of those with an undergraduate degree or a graduate degree are very comparable to those from the Census.

As for household characteristics (right panel of Table 2), our sample is definitively skewed toward low income households. While 43.4% of our sample live in households that make less than $50,000 a year, and 28.1% of our sample live in households with an annual income of $100,000 or more, the corresponding percentages from the Census data are 31% and 38%, respectively. This lower income bias in our sample is consistent with the fact that many respondents were young and/or students. The average household size of sample respondents is close to three, while the corresponding figure from the Census data is 2.7 persons per household (the Census does not provide a breakdown by number of individuals in the household, and only provides an average household size value). Our sample and the Census align fairly well with regard to households with no children (83.1% compared to 81.3%). Finally, the Census provides no information on number of vehicles per household, though the low percentage of zero-vehicle households in our sample is to be expected.

Variable	Count	%	Variable	Count	%
Individual Demographics			*Household Characteristics*		
Gender			**Household annual income**		
Female	658	64.4	Less than $25,000	266	26.1
Male	363	35.6	$25,000 to $49,999	177	17.3
Age			$50,000 to $74,999	158	15.5
18 to 29	597	58.4	$75,000 to $99,999	133	13.0
30 to 39	118	11.6	$100,000 to $149,999	156	15.3
40 to 49	101	9.9	$150,000 to $249,999	92	9.0
50 to 64	104	10.2	$250,000 or more	39	3.8
65 or older	101	9.9	**Household Size**		
Employment Type			Live alone	254	24.9
Student	530*	51.9	2 people	283	27.7
Employed	623*	61.0	3 people	150	14.7
Unemployed and not a student	138	13.5	4 or more people	334	32.7
Education			**Children (<18 years) in Household**		
Completed high-school or less	140	13.7	Yes	172	16.9
Completed some college or technical school	361	35.4	No	849	83.1
Completed undergraduate degree	348	34.1	**Vehicles per Household**		
Completed graduate degree	172	16.8	No vehicles	84	8.2
			1 vehicle	250	24.5
			2 vehicles	337	33.0
			3 vehicles	211	20.7
			4 or more vehicles	139	13.6

*270 respondents were both employed and students

Sample Distribution of Exogenous Variables: Socio-Demographic and Household Related Characteristics

Appendix C:Design of the Latent Variables

Indicators of…	Attitudinal Indicator	Response Category: *Strongly disagree* Frequency (Percent)	*Somewhat disagree* Frequency (Percent)	*Neutral* Frequency (Percent)	*Somewhat agree* Frequency (Percent)	*Strongly agree* Frequency (Percent)	Total
Driving Control	I will never ride in an AV	361 (35.4)	266 (26.0)	234 (22.9)	100 (9.8)	60 (5.9)	1021 (100.0)
	AVs will eliminate my joy of driving	192 (18.8)	243 (23.8)	267 (26.2)	235 (23.0)	84 (8.2)	1021 (100.0)
	When traveling in a vehicle, I prefer to be a driver rather than a passenger	140 (13.7)	209 (20.5)	242 (23.7)	207 (20.3)	223 (21.8)	1021 (100.0)
	AVs would make traveling by car less stressful for me	117 (11.5)	186 (18.2)	289 (28.3)	284 (27.8)	145 (14.2)	1021 (100.0)
Mobility Control	I definitely like the idea of owning my own car	26 (2.5)	63 (6.2)	112 (11.0)	206 (20.2)	614 (60.1)	1021 (100.0)
	Ride-hailing services allow me to live with fewer or no cars	248 (24.3)	210 (20.6)	321 (31.4)	166 (16.3)	76 (7.4)	1021 (100.0)
	I will use AV ride hailing services alone or with coworkers, friends, or family	140 (13.7)	209 (20.5)	242 (23.7)	207 (20.3)	223 (21.8)	1021 (100.0)
Safety Concern	I would feel comfortable having an AV pick up/drop off children without adult supervision	341 (33.4)	301 (29.5)	201 (19.7)	128 (12.5)	50 (4.9)	1021 (100.0)
	I am concerned about the potential failure of AV sensors, equipment, technology, or programs	41 (4.0)	76 (7.5)	132 (12.9)	431 (42.2)	341 (33.4)	1021 (100.0)
	I would feel comfortable sleeping while traveling in an AV	284 (27.8)	277 (27.1)	192 (18.8)	179 (17.6)	89 (8.7)	1021 (100.0)
	AVs would make me feel safer on the street as a pedestrian or as a cyclist	156 (15.3)	293 (28.7)	291 (28.5)	193 (18.9)	88 (8.6)	1021 (100.0)
Technology Savviness	I like to be among the first to have the latest technology	58 (5.7)	185 (18.1)	202 (19.8)	416 (40.7)	160 (15.7)	1021 (100.0)

Indicators of…	**Attitudinal Indicator**	**Response Category**					**Total**
		Strongly disagree	***Somewhat disagree***	***Neutral***	***Somewhat agree***	***Strongly agree***	
		Frequency (Percent)	Frequency (Percent)	Frequency (Percent)	Frequency (Percent)	Frequency (Percent)	
	Learning how to use new technologies is often frustrating for me	361 (35.4)	363 (35.5)	132 (12.9)	141 (13.8)	24 (2.4)	1021 (100.0)

Distribution of Attitudinal Indicators

Attitudinal Indicators	Loading of Indicators on Latent Constructs							
	Driving Control		Mobility Control		Safety Concern		Tech-Savviness	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
I will never ride in an AV	0.782	17.74						
AVs will eliminate my joy of driving	0.632	14.74						
When traveling in a vehicle, I prefer to be a driver rather than a passenger	0.422	8.75						
AVs would make traveling by car less stressful for me	-0.826	-18.44						
I definitely like the idea of owning my own car			0.676	10.04				
Ride-hailing services allow me to live with fewer or no cars			-0.686	-9.42				
I will use AV ride hailing services alone or with coworkers, friends, or family			0.410	7.96				
I would feel comfortable having an AV pick up/drop off children without adult supervision					0.872	23.65		
I am concerned about the potential failure of AV sensors, equipment, technology, or programs					-0.483	-14.69		
I would feel comfortable sleeping while traveling in an AV					0.886	22.04		
AVs would make me feel safer on the street as a pedestrian or as a cyclist					0.796	21.73		
I like to be among the first to have the latest technology							0.341	8.62
Learning how to use new technologies is often frustrating for me							-0.845	-11.29

Loadings of Latent Variables on Indicators

Appendix D: Mathematical Formulation of GHDM Model for Jointly Modeling Continuous, Nominal, and Ranked Outcomes

Let l be the index for the latent constructs (l=1,2,…L; L=4 in our analysis). Let the underlying stochastic latent construct be denoted by z_l^*, and we write z_l^* as a linear function of covariates:

$$z_l^* = \boldsymbol{\alpha}_l' \boldsymbol{w} + \eta_l, \tag{1}$$

where $\boldsymbol{w}$ is a $(D \times 1)$ vector of observed covariates (excluding a constant), $\boldsymbol{\alpha}_l$ is a corresponding $(D \times 1)$ vector of coefficients, and η_l is a standard normally distributed random error term. For future use, we also define the $(L \times D)$ matrix $\boldsymbol{\alpha} = (\boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2, ..., \boldsymbol{\alpha}_L)'$, and the $(L \times 1)$ vectors $\boldsymbol{z}^* = (z_1^*, z_2^*, ..., z_L^*)'$ and $\boldsymbol{\eta} = (\eta_1, \eta_2, \eta_3, \ldots, \eta_L)'$. In matrix form, we may write Equation (1) as:

$$\boldsymbol{z}^* = \boldsymbol{\alpha w} + \boldsymbol{\eta}. \tag{2}$$

We consider a multivariate normal correlation structure for $\boldsymbol{\eta}$ to accommodate interactions among the unobserved latent variables: $\boldsymbol{\eta} \sim MVN_L[\boldsymbol{0}_L, \boldsymbol{\Gamma}]$, where $\boldsymbol{0}_L$ is an $(L \times 1)$ column vector of zeros, and $\boldsymbol{\Gamma}$ is $(L \times L)$ correlation matrix. Equation (2) constitutes the structural equations model (SEM) component of the model.

Of course, we do not observed the latent construct vector $\boldsymbol{z}^*$. However, we can consider the point values (say $c_{z_l^*}$ for each latent construct z_l^*) obtained from the confirmatory factor analysis as manifestations of the stochastic latent construct z_l^*. Define the $(L \times 1)$ vector $\boldsymbol{c} = (c_{z_1^*}, c_{z_2^*}, ..., c_{z_L^*})'$. Then, the first component of the measurement equation model may be written as $\boldsymbol{c} = \boldsymbol{z}^*$. This component, in our model system, comprises four continuous dependent outcome variables. Next, let there be G nominal and rank-ordered dependent outcome variables for an individual, and let g be the index for these variables $(g = 1, 2, 3, ..., G)$. For our analysis, G=3 (one unordered nominal outcome corresponding to the duration to adoption or DAD choice and two rank-ordered outcomes corresponding to the responses to the two questions related to AV adoption). Also, let I_g be the number of alternatives corresponding to the g^{th} variable ($I_g \geq 3$) and let i_g be the corresponding index $(i_g = 1, 2, 3, ..., I_g)$. In our analysis, I_g =3 for all $g = 1,\ 2,\ 3$ since all the variables have 3 alterntives each. Consider the g^{th} variable and assume the usual random utility structure for each alternative i_g:

$$U_{gi_g} = \boldsymbol{b}'_{gi_g}\boldsymbol{x} + \boldsymbol{\vartheta}'_{gi_g}(\boldsymbol{\beta}_{gi_g}\boldsymbol{z}^*) + \varsigma_{gi_g}, \tag{3}$$

where $\boldsymbol{x}$ is an $(A \times 1)$ vector of exogenous variable (including a constant), $\boldsymbol{b}_{gi_g}$ is an $(A \times 1)$ column vector of corresponding coefficients, and ς_{gi_g} is a normal error term. $\boldsymbol{\beta}_{gi_g}$ is an $(N_{gi_g} \times L)$-matrix of variables interacting with latent variables to influence the utility of alternative i_g, and $\boldsymbol{\vartheta}_{gi_g}$ is an $(N_{gi_g} \times 1)$-column vector of coefficients capturing the effects of latent variables and their interaction effects with other exogenous variables. If each of the latent variables impacts the utility of the alternatives for each nominal variable purely through a constant shift in the utility function, $\boldsymbol{\beta}_{gi_g}$ will be an identity matrix of size L, and each element of $\boldsymbol{\vartheta}_{gi_g}$ will capture the effect of a latent variable on the constant specific to alternative i_g of nominal variable g. Let $\boldsymbol{\varsigma_g} = (\varsigma_{g1}, \varsigma_{g2}, ...\varsigma_{gI_g})'$ $(I_g \times 1$ vector), and $\boldsymbol{\varsigma_g} \sim MVN_{I_g}(\mathbf{0}, \mathbf{\Lambda_g})$. Taking the difference with respect to the first alternative, the only estimable elements are found in the covariance matrix $\breve{\mathbf{\Lambda}}_g$ of the error differences, $\breve{\boldsymbol{\varsigma}}_{\boldsymbol{g}} = (\breve{\varsigma}_{g2}, \breve{\varsigma}_{g3}, ..., \breve{\varsigma}_{gI_g})$ (where $\breve{\varsigma}_{gi} = \varsigma_{gi} - \varsigma_{g1}, i \neq 1)$. Further, the variance term at the top left diagonal of $\breve{\mathbf{\Lambda}}_g$ $(g = 1, 2, ..., G)$ is set to 1 to account for scale invariance. $\mathbf{\Lambda_g}$ is constructed from $\breve{\mathbf{\Lambda}}_{\mathbf{g}}$ by adding a row on top and a column to the left. All elements of this additional row and column are filled with values of zero. In addition, the usual identification restriction is imposed such that one of the alternatives serves as the base when introducing alternative-specific constants and variables that do not vary across alternatives (that is, whenever an element of $\boldsymbol{x}$ is individual-specific and not alternative-specific, the corresponding element in $\boldsymbol{b}_{gi_g}$ is set to zero for at least one alternative i_g). To proceed, define $\boldsymbol{U}_g = (U_{g1}, U_{g2}, ..., U_{gI_g})'$ $(I_g \times 1$ vector), $\boldsymbol{b}_g = (\boldsymbol{b}_{g1}, \boldsymbol{b}_{g2}, \boldsymbol{b}_{g3}, ..., \boldsymbol{b}_{gI_g})'$ $(I_g \times A$ matrix), and $\boldsymbol{\beta}_g = (\boldsymbol{\beta}'_{g1}, \boldsymbol{\beta}'_{g2}, ..., \boldsymbol{\beta}'_{gI_g})'$ $\left(\sum_{i_g=1}^{I_g} N_{gi_g} \times L\right)$ matrix. Also, define the $\left(I_g \times \sum_{i_g=1}^{I_g} N_{gi_g}\right)$ matrix $\boldsymbol{\vartheta_g}$, which is initially filled with all zero values. Then, position the $(1 \times N_{g1})$ row vector $\boldsymbol{\vartheta}'_{g1}$ in the first row to occupy columns 1 to N_{g1}, position the $(1 \times N_{g2})$ row vector $\boldsymbol{\vartheta}'_{g2}$ in the second row to occupy columns $N_{g1}+1$ to $N_{g1} + N_{g2}$, and so on until the $(1 \times N_{gI_g})$ row vector $\boldsymbol{\vartheta}'_{gI_g}$ is appropriately positioned. Further, define $\boldsymbol{\varpi}_g = (\boldsymbol{\vartheta}_g \boldsymbol{\beta}_g)$ ($I_g \times L$ matrix), $\vec{G} = \sum_{g=1}^{G} I_g$, $\tilde{G} = \sum_{g=1}^{G}(I_g - 1)$, $\boldsymbol{U} = \left(\boldsymbol{U}_1', \boldsymbol{U}_2', \ldots, \boldsymbol{U}_G'\right)'$ ($\vec{G} \times 1$ vector), $\boldsymbol{\varsigma} = (\boldsymbol{\varsigma}_1, \boldsymbol{\varsigma}_2, \ldots \boldsymbol{\varsigma}_G)'$ ($\vec{G} \times 1$ vector), $\boldsymbol{b} = (\boldsymbol{b}_1', \boldsymbol{b}_2', \ldots, \boldsymbol{b}_{\boldsymbol{G}}')'$ ($\vec{G} \times A$ matrix), $\boldsymbol{\varpi} = (\boldsymbol{\varpi}_1', \boldsymbol{\varpi}_2', \ldots, \boldsymbol{\varpi}_G')'$ ($\vec{G} \times L$ matrix), and $\boldsymbol{\vartheta} = \text{Vech}(\boldsymbol{\vartheta}_1, \boldsymbol{\vartheta}_2, \ldots, \boldsymbol{\vartheta}_G)$ (that is, $\boldsymbol{\vartheta}$ is a column vector that includes all elements of the matrices $\boldsymbol{\vartheta}_1, \boldsymbol{\vartheta}_2, \ldots, \boldsymbol{\vartheta}_G$). Then, in matrix form, we may write Equation (1) as:

$$\boldsymbol{U} = \boldsymbol{bx} + \boldsymbol{\varpi}\,\boldsymbol{z}^* + \boldsymbol{\varsigma}, \qquad \text{where } \boldsymbol{\varsigma} \sim MVN_{\vec{G}}(\mathbf{0}_{\vec{G}}, \boldsymbol{\Lambda}).$$

$$\boldsymbol{\Lambda} = \begin{bmatrix} \boldsymbol{\Lambda}_1 & \boldsymbol{\Lambda}_{12} & \boldsymbol{\Lambda}_{13} & \boldsymbol{\Lambda}_{14} & \cdots \boldsymbol{\Lambda}_{1\boldsymbol{G}} \\ \mathbf{0} & \boldsymbol{\Lambda}_2 & \boldsymbol{\Lambda}_{23} & \boldsymbol{\Lambda}_{24} & \cdots \boldsymbol{\Lambda}_{2\boldsymbol{G}} \\ \mathbf{0} & \mathbf{0} & \boldsymbol{\Lambda}_3 & \boldsymbol{\Lambda}_{34} & \cdots \boldsymbol{\Lambda}_{3\boldsymbol{G}} \\ \vdots & \vdots & \vdots & \vdots & \ldots \vdots \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \ldots \ldots \boldsymbol{\Lambda}_{\boldsymbol{G}} \end{bmatrix} (\vec{\boldsymbol{G}} \times \vec{\boldsymbol{G}} \text{ matrix}).$$

The off-diagonal elements of the $\boldsymbol{\Lambda}$ matrix capture the correlations of the unobserved factors across the alternatives of the various nominal variables.

To proceed further, we may write the components of the joint model as follows:

$$\boldsymbol{z}^* = \boldsymbol{\alpha w} + \boldsymbol{\eta} \quad \text{(SEM component)}, \tag{4}$$

$$\boldsymbol{c} = \boldsymbol{z}^* \quad \text{(MEM component)}, \tag{5}$$

$$\boldsymbol{U} = \boldsymbol{bx} + \boldsymbol{\varpi}\,\boldsymbol{z}^* + \boldsymbol{\varsigma}, \quad \text{(MEM component)}, \tag{6}$$

with $Cov \begin{pmatrix} \boldsymbol{\eta} \\ \boldsymbol{\varsigma} \end{pmatrix} = \boldsymbol{\Psi} = \begin{bmatrix} \boldsymbol{\Gamma} & \boldsymbol{\Omega} \\ \boldsymbol{\Omega}' & \boldsymbol{\Lambda} \end{bmatrix}$ ($E \times E$ matrix), $E = L + \vec{G}$.

$\boldsymbol{\Omega}$ in the equation above represents the ($L \times \vec{G}$) correlation elements between the $\boldsymbol{\eta}$ and $\boldsymbol{\varepsilon}$ error elements (this recognizes the endogeneity of the latent constructs in the system). To develop the reduced form equations, replace the right side of the SEM component into the MEM components to obtain the following system:

$$\boldsymbol{c} = \boldsymbol{\alpha w} + \boldsymbol{\eta} \tag{7}$$

$$\boldsymbol{U} = \boldsymbol{bx} + \boldsymbol{\varpi}\,(\boldsymbol{\alpha w} + \boldsymbol{\eta}) + \boldsymbol{\varsigma} = \boldsymbol{bx} + \boldsymbol{\varpi\alpha w} + \boldsymbol{\varpi\eta} + \boldsymbol{\varsigma} \tag{8}$$

Now, consider the $[(E \times 1)]$ vector $\boldsymbol{cU} = \begin{pmatrix} \boldsymbol{c} \\ \boldsymbol{U} \end{pmatrix}$ Let $\boldsymbol{d} = (\boldsymbol{\varpi}, \boldsymbol{IDEN_G})'$, an $(E \times \vec{G})$ -matrix. Define

$$\boldsymbol{B} = \begin{bmatrix} \boldsymbol{B_c} \\ \boldsymbol{B}_U \end{bmatrix} = \begin{bmatrix} \boldsymbol{\alpha w} \\ \boldsymbol{bx} + \boldsymbol{\varpi\alpha w} \end{bmatrix} \text{ and } \boldsymbol{\Sigma} = \begin{bmatrix} \boldsymbol{\Sigma_c} & \boldsymbol{\Sigma_{cU}} \\ \boldsymbol{\Sigma'_{cU}} & \boldsymbol{\Sigma_U} \end{bmatrix} = \begin{bmatrix} \boldsymbol{\Gamma} & \boldsymbol{\Omega} + \boldsymbol{\Gamma\varpi'} \\ \boldsymbol{\Omega'} + \boldsymbol{\varpi\Gamma'} & \boldsymbol{d}'\boldsymbol{\Psi d} \end{bmatrix}. \tag{9}$$

Then $cU \sim \boldsymbol{MVN_E}(\boldsymbol{B},\boldsymbol{\Sigma})$ is the multivariate joint distribution of the main outcomes and the latent factor continuous variables.

Appendix E: GHDM Model Estimation

In the context of the nominal unordered variable in our analysis, i.e. the outcome related to the DAD dimension, assume that the individual under consideration chooses alternative m_g corresponding to the g^{th} nominal outcome. Under the utility maximization theory, $U_{gi_g} - U_{gm_g}$ must be less than zero for all $i_g \neq m_g$ corresponding to the g^{th} nominal variable, since the individual chose alternative m_g. Let $u_{gi_g m_g} = U_{gi_g} - U_{gm_g} \ (i_g \neq m_g)$, and stack the latent utility differentials into a vector $\boldsymbol{u_g} = \left[\left(u_{g1m_g}, u_{g2m_g}, ..., u_{gI_g m_g} \right)'; i_g \neq m_g \right]$. However, for the case of a rank-ordered nominal variable (along the AVD dimensions), the utility differentials are arrived at based on the order of the ranking. In particular, let $\boldsymbol{r_g}$ be a specific rank ordering of the alternatives corresponding to the g^{th} nominal variable. That is, $r_g^{\,1}$ is the first-ranked alternative, $r_g^{\,2}$ is the second-ranked alternative and so on. $R_{\boldsymbol{r}}$ denotes the event that the alternatives are ranked in the order $\boldsymbol{r}$ by the individual. According to the random utility maximization framework, the following relationship must hold for $R_{\boldsymbol{r}}$,

$$R_{\boldsymbol{r},g} : U_{i_g r^2} - U_{i_g r^1} < 0, U_{i_g r^3} - U_{i_g r^2} < 0, ..., U_{i_g r^{I_g}} - U_{i_g r^{I_g - 1}} < 0$$

The latent utility differentials for the rank-ordered nominal outcomes are stacked in a similar fashion as the unordered nominal outcome. Now, define $\boldsymbol{u} = \left([\boldsymbol{u}_1]', [\boldsymbol{u}_2]', ..., [\boldsymbol{u_G}]' \right)'$, where the utility differentials can either be based on unordered nominal outcomes or rank-ordered nominal outcomes. We now need to develop the distribution of the vector $\boldsymbol{cu} = (\boldsymbol{c}', \boldsymbol{u}')'$ from that of $\boldsymbol{cU} = (\boldsymbol{c}', \boldsymbol{U}')'$. To do so, define a matrix **M** of size $\left[\boldsymbol{L} + \tilde{\boldsymbol{G}} \right] \times \left[\boldsymbol{L} + \ddot{\boldsymbol{G}} \right]$. Fill this matrix with values of zero. Then, insert an identity matrix of size L into the first L rows and L columns of the matrix **M**. Next, consider the rows from $\boldsymbol{L}+1$ to $\boldsymbol{L}+\boldsymbol{I}_1 - 1$, and columns from $\boldsymbol{L}+1$ to $\boldsymbol{L}+\boldsymbol{I}_1$. These rows and columns correspond to the first nominal variable. If this nominal variable is a pure unordered (single choice) variable, insert an identity matrix of size $(I_1 - 1)$ after supplementing with a column of '-1' values in the column corresponding to the chosen alternative. Next, rows $\boldsymbol{L}+\boldsymbol{I}_1$ through $\boldsymbol{L}+\boldsymbol{I}_1+\boldsymbol{I}_2 - 2$ and columns $\boldsymbol{L}+\boldsymbol{I}_1+1$ through

$\boldsymbol{L}+\boldsymbol{I}_1+\boldsymbol{I}_2$ correspond to the second nominal variable. Again position an identity matrix of size (I_2-1) after supplementing with a column of '-1' values in the column corresponding to the chosen alternative for the second nominal variable (if this variable is again an unordered single choice variable). However, if any of the nominal variables is a rank-ordered decision variable, then undertake the following method to fill in each of such sub-matrices: place a value of '–1' at the column corresponding to the first ranked alternative and '1' at the column corresponding to the second ranked alternative. Similarly, in the second row, place a value of '–1' at the column corresponding to the second ranked alternative and '1' at the column corresponding to the third ranked alternative. Continue this procedure for $(\boldsymbol{I}_g-1)$ rows (if the g^{th} nominal variable happens to be a rank-ordered variable). Therefore, based on whether the sub-matrix within the matrix **M** corresponds to an unordered nominal variable or a rank-ordered nominal variable, undertake one of the two respective ways as described to fill in these sub-matrices. Continue this procedure for all *G* nominal variables (again, nominal variables here include both, unordered and rank-ordered variables). With the matrix **M** as defined, we can write $\boldsymbol{cu} \sim MVN_{L+\tilde{G}}(\tilde{\boldsymbol{B}},\tilde{\boldsymbol{\Omega}})$, where $\tilde{\boldsymbol{B}}=\mathbf{M}\boldsymbol{B}$ and $\tilde{\boldsymbol{\Sigma}}=\mathbf{M}\boldsymbol{\Sigma}\mathbf{M}'$. Next, partition the vector $\tilde{\boldsymbol{B}}$ into components that correspond to the mean of the vectors $\boldsymbol{c}$ (for the continuous latent variables) and $\boldsymbol{u}$ (for the nominal outcomes), and the matrix $\tilde{\boldsymbol{\Sigma}}$ into the corresponding variances and covariances:

$$\tilde{\boldsymbol{B}}=\begin{bmatrix}\tilde{\boldsymbol{B}}_c\\ \tilde{\boldsymbol{B}}_u\end{bmatrix},\ (\boldsymbol{L}+\tilde{\boldsymbol{G}})\times 1 \text{ vector,} \qquad \text{and} \qquad \tilde{\boldsymbol{\Sigma}}=\begin{bmatrix}\tilde{\boldsymbol{\Sigma}}_c & \tilde{\boldsymbol{\Sigma}}_{cu}\\ \tilde{\boldsymbol{\Sigma}}'_{cu} & \tilde{\boldsymbol{\Sigma}}_u\end{bmatrix},\ (\boldsymbol{L}+\tilde{\boldsymbol{G}})\times(\boldsymbol{L}+\tilde{\boldsymbol{G}})$$

vector

The conditional distribution of $\boldsymbol{u}$, given $\boldsymbol{c}$, is MVN with mean $\ddot{\boldsymbol{B}}_u=\tilde{\boldsymbol{B}}_u+\tilde{\boldsymbol{\Sigma}}'_{cu}\,\tilde{\boldsymbol{\Sigma}}_c^{-1}\left(\boldsymbol{c}-\tilde{\boldsymbol{B}}_c\right)$ and variance $\ddot{\boldsymbol{\Sigma}}_u=\tilde{\boldsymbol{\Sigma}}_u-\tilde{\boldsymbol{\Sigma}}'_{cu}\,\tilde{\boldsymbol{\Sigma}}_c^{-1}\tilde{\boldsymbol{\Sigma}}_{cu}$. Then the likelihood function may be written as (where $\mathbf{0}_{\tilde{G}}$ is a $\tilde{G}\times 1$-column vector of zeros):

$$\begin{aligned}\boldsymbol{L}(\boldsymbol{\delta}) &= \boldsymbol{f}_L(\boldsymbol{c}\,|\,\tilde{\boldsymbol{B}}_c,\tilde{\boldsymbol{\Sigma}}_c)\times\Pr\left[\boldsymbol{u}\le\mathbf{0}_{\tilde{G}}\right], \\ &= \boldsymbol{f}_L(\boldsymbol{c}\,|\,\tilde{\boldsymbol{B}}_c,\tilde{\boldsymbol{\Sigma}}_c)\times\int_{\boldsymbol{D}_r}\boldsymbol{f}_{\tilde{G}}(\boldsymbol{r}\,|\,\ddot{\boldsymbol{B}}_u,\ddot{\boldsymbol{\Sigma}}_u)\,\boldsymbol{dr},\end{aligned} \tag{10}$$

where the integration domain $\boldsymbol{D}_r$ is simply the multivariate region of the elements of the $\boldsymbol{u}$ vector determined by the range $(-\infty_{\tilde{G}},\mathbf{0}_{\tilde{G}})$ for the utility differences for the nominal outcomes. $\boldsymbol{f}_L(\boldsymbol{c}\,|\,\tilde{\boldsymbol{B}}_c,\tilde{\boldsymbol{\Sigma}}_c)$ is the MVN density function of dimension $\boldsymbol{L}$ with a mean of $\tilde{\boldsymbol{B}}_c$ and a covariance of $\tilde{\boldsymbol{\Sigma}}_c$, and evaluated at $\boldsymbol{c}$. The likelihood function for a sample of *Q* decision-makers is obtained as the product of the individual-level likelihood functions. The above likelihood function involves the evaluation of a $\tilde{\boldsymbol{G}}$-dimensional upper-truncated integral for each decision-maker, which can be computationally expensive. However, Bhat's (2018) matrix-based approximation method for evaluating multivariate normal cumulative distribution (MVNCD) function was employed to evaluate this integral, which provides an efficient and tractable formulation to approximate high dimensional MVNCD integral.

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