EVALUATING THE EFFECTS OF CONSUMER'S PERCEPTIONS OF SAFETY AND PRODUCTIVE USE OF TIME ON THE INTENTION TO ADOPT AUTONOMOUS VEHICLE TECHNOLOGY

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ABSTRACT

The race to build fully self-driving cars, or autonomous vehicles (AVs), is no longer in the developmental stages. While AVs bring along a promise of reduction in crashes, costs of congestion, energy consumption, and pollution, there is an apparent disparity between the automotive industry's expectation of AV demand and consumer's perspectives on AV benefits. Therefore, it is an immediate necessity to understand what factors drive a user towards adoption of AV technology. In this study, we undertook a comprehensive analysis of willingness to adopt and pay for AV by providing a latent-class and latent variable analysis to identify the segment of the population which is more likely to adopt and pay a premium for an AV. Our results show that the appeal of autonomous vehicles, to consumers who are willing to pay more, is deriving its utility from perceptions of a higher propensity to use one's travel time productively by engaging in activities while commuting, as well as, from the perceptions of higher safety provided by these technologies. The segmentation results suggest that is important to study the effect of latent constructs as they isolate the individuals who're more tech-savvy and seek variety in their life for the adoption of AVs. However, these individuals still form a segment share of 55%, while the rest of the population is unwilling to pay a premium. Results from this study provide an inspiration to consider user-perception to better estimate AV adoption scenarios.

Keywords: latent-segmentation, latent variables, AV adoption, safety perception, productive use of travel time.

1. INTRODUCTION

The use of AVs has an enormous potential to allow for: 1. providing productive use of the time otherwise spent in driving, and 2. providing superior safety with the invention of new technologies. Long-term AV benefits include a reduction in number of crashes, cost of congestion, energy consumption, and pollution. These potential benefits influence the models of vehicle ownership and patterns of land use and may create new markets and economic opportunities. Yet they also pose risks and challenges related to safety, cybersecurity, privacy, liability and much more. Managing the risks and maximizing the benefits of AVs requires carefully designed policies that are based on objective research related to human acceptance of new technologies and driver's knowledge, attitudes and perceptions towards AVs. See for example Becker and Axhausen (2017) for a literature review of surveys with a focus on AVs (that is, higher automation levels).

Transport policymakers in various countries are increasingly interested in the large-scale implementation of AVs. However, policy development regarding AVs is hindered by uncertainties related to the societal constraints and conditions for AV deployment and the contribution of such deployments towards general transportation goals. One such constraint that demands immediate attention of the researchers is the users' perception of safety and other potential benefits that AVs may provide. Not only has the consumers' interest and trust in AVs dropped in the past two years (Abraham et al., 2017; J.D. Powers, 2017; Deloitte, 2017), but these studies also point to increased disbelief in AV safety and skepticism toward the ability of this technology to work perfectly. From a transportation planning perspective, the apparent mismatch between the automotive industry pace and consumers' perspectives leads to highly uncertain adoption scenarios. Hence, to build AV adoption forecasts, it is urgent to understand the relationship between individuals' perceptions and the resulting AV technology acceptance.

Uncertainty in terms of safety provided by these innovative technologies is burdened by the fact that roughly 2.2 million Americans are injured in crashes each year, while there are over 30,000 fatalities (NHTSA, 2014). The economic cost of these crashes is roughly $300 billion, which is approximately three times the U.S.'s annual congestion costs (Cambridge Systematics, 2011). Autonomous vehicles (AVs) have the potential to provide a solution to the risks associated to on-road travel, and to reduce a high proportion of the 90% of crashes that result from driver error (NHTSA, 2008). Moreover, the research efforts have skipped the study of consumer understanding of how the AVs will affect their activity pattern and provide them with the opportunity to use the travel time more effectively.

Many researchers have studied acceptance of advanced vehicle technologies from the buyers' perspectives (Harper et al., 2016; Bansal et al., 2016; Nordhoff et al., 2016; Kyriakidis et al., 2015; Underwood, 2014; Silberg et. al., 2012). Despite the growing body of travel behavior literature on individual's preferences toward automation (Bansal et al., 2016) and AVs (Krueger et al., 2016; Haboucha et al., 2017), there are scarce to non-existent studies that simultaneously investigate safety perception determinants and intention to adopt AVs (Becker and Axhausen, 2017). Moreover, these studies often overlook the extent to which automation technologies already exist in the current vehicles. With the availability of lane assist, parking assist and semi autopilot, many users have an existing understanding of the benefits provided by automation features in vehicles. This ownership and experience with automation features and the safety provided permeates into user perception of future availability of a fully autonomous vehicle.

Although some surveys collect data on both AV preferences and safety concerns (Kyriakidis et al., 2015), the relationship between these variables is seldom modeled. An exception is the study from Lavieri et al. (2017) that incorporates individuals' concerns about technology failure in an AV adoption model. These authors observe that safety concerns have a negative impact on the willingness to adopt AV technology, yet they are unable to identify the determinants of such concerns. Not only are AVs attractive for the safety provided, but they also have other potential benefits such as providing more time to involve in productive activities, such as work, during the commute. The current study aims to investigate the effects of individuals' safety perceptions, perception of productive use of travel time and current use of automation on the willingness to adopt AV technology. The model results are used to evaluate possible changes in AV adoption rates as a function of the confidence about this technology as perceived by different segments of the population.

The remainder of this paper is organized as follows. In section 2, we provide an overview of earlier studies on willingness to pay for automation, the role of safety perception on preferences toward AVs, the productive use of travel time and ownership of automation features, followed by a positioning of our study in Section 2.5. Section 3 gives a detailed description of the data used for this study. Section 4 provides the conceptual and methodological details for the proposed behavioral framework. Results of the model estimation efforts are provided in section 5. Policy implications are discussed in Section 7 followed by conclusions in the final section.

2. LITERATURE REVIEW

2.1 Willingness to pay for automation

The scarcity of studies focusing on understanding the impact of public perception on adoption of AV technologies is evident from the fact the most studies are unilateral in understanding the aspect of preferences towards AVs, considering the impacts of only the observed factors such as cost, safety and travel time on AV adoption. In particular, several recent studies (Kyriakidis et al., 2015; Underwood, 2014; Wallace and Silberg, 2012) attempt to understand how consumer preferences for attributes, such as safety and travel time, shape the demand for driverless cars and to what extent are they willing to pay an additional amount. Kyriakidis et al. (2015) survey of opinions from 5000 respondents from 109 countries gave an insightful result: 22 percent of the respondents did not want to pay any additional price for a fully automated navigation system, whereas 5 percent indicated they would be willing to pay more than $30,000. Another such study in the past was conducted by Schoettle and Sivak (2014) focusing on the residents of China, India, Japan, United States, United Kingdom, and Australia. The authors found that most respondents expressed a desire to own an autonomous vehicle, but with a larger proportion unwilling to pay extra for the technology. They also raised high levels of concern about riding in self-driving vehicles, with the most pressing issues involving those related to equipment or system failure.

Most studies only restrict the effort to differentiate between various levels of automation to estimate the users' willingness to pay. Bansal et al. (2016) find that for their sample of 347 residents of Austin, Texas, willingness to pay (WTP) for full automation is $7253, while WTP for partial automation of $3300. Interesting to notice is the fact that not only more than 80% of the respondents did not show interest in using SAVs at costs higher than current carsharing prices, but also that equipment failure was the main concern of respondents. Daziano et al. (2017) estimate that the average household is willing to pay a significant amount for automation: $3500 for partial automation and $4900 for full automation. The variation is quite substantial in the respondents' valuation of the technology. Some are not willing to pay anything for either type of automation, while others that are more knowledgeable about current abilities of automation are willing to pay a great deal for full automation.

However, some studies analyze the impact of socio-demographic characteristics, in addition to awareness about automation, of the survey respondents on the willingness to pay for automation. Bansal and Kockelman (2015) conclude that older and more experienced drivers expressed lower WTP for connectivity and all automation levels, whereas higher-income and more safety-cautious persons (e.g., those having experienced a fatal crash and/or are supportive of speed checks on vehicles) are willing to pay more to add these technologies. Although public opinion regarding buying/using AVs and acceptance and/or trust for the technology is important to research for the implementation of this new technology in the market, recent studies have mostly considered the opinions of drivers, not of other road-users. An interesting analysis is performed by Bansal and Kockelman (2015) to forecast Americans' long term (year 2015–2045) adoption levels of CAV technologies under eight different scenarios based on 5% and 10% annual drops in technology prices; 0%, 5%, and 10% annual increments in Americans' willingness to pay (WTP); and changes in government regulations (e.g., mandatory adoption of connectivity on new vehicles). Overall, simulations suggest that, without a rise in most people's WTP, or policies that promote or require technologies, or unusually rapid reductions in technology costs, it is unlikely that the U.S. light duty vehicle fleet's technology mix will be anywhere near homogeneous by the year 2045.

2.2 The role of safety perception on preferences toward AVs

Automated vehicle technologies are designed to be able to sense and make judgments about the external environment (e.g. road signs, other road-users, traffic density) and actions the vehicle should take. In an autonomous vehicle, various functions are controlled by software and hardware allowing those functions to operate independent of a driver. This technology can reduce physical and mental stress for drivers, as well as increase safety for all road-users and reduce fuel consumption (Mersky and Samaras, 2016; Keen, 2013). However, these judgments are dependent on the proper functioning of all cameras, lasers, sensors, and radar scanners that comprise the technology. Fully autonomous vehicles are still in the research-and-development phase with numerous ongoing experiments. Some studies seek to improve this technology by addressing all the risks associated with it, for example, the detection of other vehicles and road users (Häne et al., 2015; Litman, 2015; Levinson et al., 2011). While others, (Merat and Lee (2012)) investigate interactions between human-drivers and autonomous vehicles and conclude that automation cannot substitute flawlessly for a human driver, nor the driver can safely accommodate the limitations of automation.

Despite their potential benefits, AVs are currently affected by a number of limitations that technology has not yet been able to overcome (Robertson et. al., 2012). For instance, these types of vehicles are unable to navigate in poor weather conditions where rain or snow may interfere with the proper functioning of vehicle sensors or obscure road markings; instead they must rely on capable drivers to take control (Kovacs, 2016). Although several manufacturers are testing AVs in winter conditions, successful deployment may still take a while. Initial studies of driver behavior and vehicle safety features have suggested that driver knowledge and familiarity with AV technology generally, and self-driving technology specifically, is quite low despite the emergence of many AV technologies since the 1990s (Robertson et al., 2012; Schoettle and Sivak, 2014). Further evidence has emerged in the past few years that demonstrates the propensity of drivers to modify their driving habits in unacceptable or more dangerous ways and increase their risk of collision when using new technology by speeding, not paying attention to the driving task, or in other ways circumventing the safety benefits of technology (Rudin-Brown et al., 2011; Robertson et al., 2012).

The overview above indicates that earlier studies have provided important insights that aid our understanding of AV adoption. However, the overall knowledge base about impact of safety perception on the willingness to adopt is still limited in many ways. First, the impact of safety perception has been overlooked in the studies analyzing AV adoption scenarios and users' willingness to pay to adopt AV technologies. Theories of behavioral modification emphasize that engineering measures alone may not be enough to guarantee safety increases, and that human responses to safety measures may have the greatest influence on whether technological advances translate to market penetration of AVs. In this context, behavioral adaptation in willingness to pay refers to ways that a user may perceive this safety provided that he or she thinks influence crash risk. Second, as the public learns more about AVs and more technological experiences start spilling into the public domain, these perceptions, and potential behavioral responses are apt to change. For example, individuals may change their perception or demand towards AVs when they see their neighbors, friends and coworkers adopt AVs, with great success. Alternatively, a well-publicized accident involving an AV could set adoption rates back years. Therefore, willingness to pay derives major feedback from the safety perceptions of these AVs by individuals.

2.3 Productive use of Travel Time

About 80% of U.S. workers are assumed to lose around fifty minutes due to commuting, which could otherwise be spent in productive activities (Silberg *et.al.* 2012). Autonomous vehicles are supposed to take away the stress of driving and having the luxury of not being completely aware of the surroundings, thereby giving the rider the ability to focus on other activities in the vehicle. These activities include working, sleeping, watching videos or talking to other passengers. This is assumed to result in a substantial reduction in Value of (travel) Time (VOT). However, Singleton (2018) argues that the productive use of travel time may not increase as much, due to the restrictions imposed by vehicular design and in-car space limitations to involve in productive tasks. Instead, the author motivated the idea that the attenuation in VOT is caused by "well-being" of the rider through reduced driving stress. Irrespective of the cause, the positive valuation of the time spent on road may provide enough motivation for consumers to adopt AVs. Travel-time savings could result in longer commute for those who perceive this as an opportunity to work or perform recreational activities during commute, and for others, it could mean more time to relax at home or spend more time at work. Therefore, willingness to adopt and pay for AVs derives value from the potential time savings and productive use of travel time benefits.

2.4 Ownership of automation features

A behavior that is often overlooked by the studies is the effect on AV adoption behavior by the current level of automation available to the consumer. Individuals currently driving a *Prius* may not be as willing to adopt an AV as those owning a *Tesla*. This behavior is often derived from the underlying satisfaction that the user may have with features currently available in the market, such as lane assist and parking assist. Understanding how this behavior of currently owning a vehicle with automated features motivates the adoption of a fully autonomous vehicle and how this ownership interacts with the other considerations of safety perception and productive use of travel time has not been done previously and may provide us interesting insights into this realm of study.

2.5 The Current Study

The current paper builds on previous literature and develops a multivariate model to investigate the determinants of individuals' willingness to adopt AV technology. The analysis is based on data from the Dallas-Fort Worth Metropolitan Area (DFW), Texas, United States. The data used in the study is drawn from an online survey, developed and administered by the authors in the fall of 2017, of 1,559 commuters in the DFW area. The survey collects information about current and future transportation choices, socio-economic and demographic characteristics, and beliefs and behaviors related to transportation situations. Some of the information provided by the survey data is beyond the scope of the current study, hence only those responses were taken into account which impact user behavior regarding AV adoption.

The study develops a model of willingness to adopt an AV for an individual as a function of unobserved lifestyle stochastic latent constructs, and observed opinions on productive use of time, safety perception and current levels of automation and socio-demographic variables. The individual was asked to imagine that he/she was planning to buy a new car and that AVs were available and were already used by all ride-hailing companies. The respondent could choose between four alternatives, which formed the four categories for the willingness to adopt an AV as a nominal dependent variable. Underlying latent psychological constructs representing technology-savviness, time-sensitivity and variety seeking are used to capture individual taste heterogeneity and create classes of individuals with similar behavior and response to AV adoption. The respondents were also asked questions about how self-driving vehicles are appealing to them based of the travel time use benefits and safety perceptions. Based on these responses, the perceptions of AV benefits were calculated and used as determinants of willingness to adopt AVs.

The framework utilizes an endogenous latent-class segmentation methodology as given by Bhat (1997), to account for group taste heterogeneity based on the assumption that groups of individuals with contrasting tech-savviness, variety seeking and time-sensitivity behaviors may differ in the way they evaluate possible benefits of autonomous technologies to inform their decision of future AV adoption. In the methodology provided by Bhat (1997), any number of segment-specific choice models can be estimated and the number of segments can be decided using the best AIC or BIC values. However, we limit the efforts to a two-segment model where the individuals are assigned to these segments in a probabilistic fashion incorporating their tech-savviness, time-sensitivity and variety seeking lifestyle propensity. Within each of these segments, a specification is developed to study the effect of safety perception, productive use of travel time and currently level of automation to understand the individuals' willingness to adopt AV. The model results are used to evaluate possible changes in AV adoption rates as a function of the confidence about this technology as perceived by different segments of the population. We also identify how each of the latent-class segments maps to adoption rates.

3. DATA DESCRIPTION

The data used for the analysis was obtained through a web-based survey conducted in DFW. The target population of the survey was commuters; screening questions were used to ensure that criterion was met. In the second section, attitudinal questions were used to identify the individual's level of tech-savviness, time-sensitivity and variety seeking. In the third section, individuals were asked about miles driven annually, number of vehicles available in the household, if any of the vehicles was hybrid or electric, and whether they had automation features (such as lane keeping assist). Finally, in section four, respondents were presented with an AV definition and had the option to watch a 90-second educational video explaining how AVs will likely operate. Then, hypothetical scenarios regarding AV adoption and use were presented and the respondents were asked to choose the alternative that would best describe their behavior. Four of these questions are used in this study. The first question asked the individual to imagine that he/she was planning to buy a new car and that AVs were available and were already used by all ride-hailing companies. The respondent could choose between five alternatives: (a) I would buy a regular vehicle (that is not self-driving). I still want to drive myself; (b) I would buy a self-driving car only if it was exactly the same price as a regular vehicle; (c) I would buy a self-driving car only if it was no more than $5,000 dollars more expensive than a regular vehicle; and (d) I would buy a self-driving car even if it was more than $5,000 dollars more expensive than a regular vehicle. The second question asked the respondent to rate (5-point Likert scale) how much he/she agreed (or disagreed) with the statement "I believe I would be safe from crashes in a self-driving vehicle". The third question asked the respondent to rate (5-point Likert scale) how much he/she agreed (or disagreed) with the statement "Self-driving vehicles are appealing because they will allow me to use my travel time more effectively". The fourth question asked the respondent give binary responses to a whether or not their current vehicle provides any or all of the automated features provided in the list, including Emergency braking assist, Lane keeping assist or lane departure warning system, Lane change assist, Automatic parking assist and Collision warning system. These questions are used to determine the effect of safety perception, productive use of travel time and level of automation (along with other exogenous variables) on willingness to adopt an AV by the proposed model described in the next section.

Table 1 presents the socio-demographic distribution of the sample. A comparison of the sample with the employed population of DFW (as characterized by the U.S. Census Bureau, 2018) indicates that the survey has an over-representation of males (58.62% in the survey compared to 54.00% from the Census data), individuals between 45 and 64 years of age (52.28% compared to 35.80%), Non-Hispanic Whites (75.11% compared to 51.50%), and individuals with bachelor's or post-graduate degrees (75.68% compared to 33.70%). We also observe that the majority of the sample corresponds to non-students (91.11%) and full time-employees (81.65%). Finally, in terms of household income and household composition, we are unable to compare the statistics from our survey with the Census data, because the latter provides income and household composition data only for all households (while our survey is focused on households with at least one worker with a primary workplace outside home). However, the sample statistics do suggest a skew toward individuals from higher income households and multi-worker households. Overall, there are many possible reasons for the socio-demographic differences between our sample and the Census data. For example, the main topic of the survey was autonomous vehicles, which may be of more interest to highly educated males. Also, the survey was conducted strictly through an online platform and the largest mailing list used in the distribution was of toll-road users, who are likely to be individuals with higher values of time that then correlates with the specific characteristics of our sample. In any case, while the general descriptive statistics of AV adoption and use cannot be generalized to the DFW population, the individual level models still provide important insights on the relationship between adoption of autonomous vehicles and socio-demographic/lifestyle characteristics.

4. MODELING METHODOLOGY

The framework encompasses three attitudinal and lifestyle latent constructs, which represent attitudes and lifestyle behavior of the individuals. Tech-savviness is used to capture a specific representation of individual unobserved heterogeneity intrinsically associated with familiarity, acceptance, and willingness to adopt new technologies. Time-sensitivity represents individual's constraint of a busy schedule on the daily activity pattern. This is important to capture availability to participate in new activities being dependent on the non-flexible schedule of individuals. The third construct, variety-seeking lifestyle propensity (VSLP) represents the individual's interest in exploration, and his/her openness to new experiences and changes. This construct has also been used in a past ride-hailing study (Alemi et al., 2017) and is important to capture intrinsic heterogeneity in the willingness to deviate from travel habits and mode inertia (Tudela et al., 2011; Rieser-Schüssler and Axhausen, 2012). For example, individuals who use vehicles with automation features and do not feel constrained by time (group 1), may have different preferences compared to a group (group 2) of individuals that does not drive vehicles with automation features and feel constrained by time. Group 1 is likely to have higher adoption rates for AVs and a higher willingness to pay (WTP) as well, as compared to group 2, which may be inclined towards new technology but may not be willing to pay a premium for the automated technology. Further, the intensity with which the perception of AV safety may influence preferences toward AV adoption might also differ across these groups.

4.1 Group heterogeneity: Latent segments based on lifestyle

The modeling framework consists of two primary components, namely, the Generalized Heterogeneous Data Model (GHDM) and the latent segmentation model (as explained in the next section). Within the GHDM, one of the sub-model is a latent structural equation model (SEM). In the latent SEM, the latent psychological constructs are represented as linear functions of exogenous variables with the usual stochastic error terms. In the SEM, the ordinal variables available in the data are used as indicators to the latent constructs. The results of this estimation provide us with expected values of the latent constructs which are used in the next step of the methodology to formulate the segments.

However, because the emphasis of this study is on the latent segmentation model, the presentation of the methodology in the next section focuses on the second component of the model system. Details about the GHDM formulation to model the latent constructs can be found in Bhat (2015a). The GHDM is estimated using the Maximum Approximate Composite Marginal Likelihood (MACML) approach (Bhat, 2011).

4.2 Latent Segmentation

The behavioral framework employs the endogenous market segmentation approach to accommodate systematic heterogeneity in a practical manner not by suppressing higher-order interaction effects of segmentation variables (on preference and response to level-of-service measures), but by reducing the dimensionality of the segment-space. Each segment, however, is allowed to be characterized by a large number of segmentation variables. The appropriate number of segments representing the reduced segment-space is determined statistically by successively adding an additional segment until a point is reached where an additional segment does not result in a significant improvement in fit. Individuals are assigned to segments in a probabilistic fashion based on the segmentation variables. The approach jointly determines the number of segments, the assignment of individuals to segments, and segment-specific choice model parameters. We use a multinomial logit formulation for modeling segment membership and a multinomial probit formulation for modeling segment specific choice of AV adoption. Bhat (1997) as mentioned before inspires this methodology. The model for willingness to adopt an AV with endogenous segmentation rests on the assumption that there are *S* relatively homogenous segments in the AV adoption market (*S* is to be determined); within each segment, the pattern of intrinsic choice preference is identical across individuals. However, there are differences in intrinsic preference patterns among the segments. Thus, there is a distinct AV adoption choice model for each segment *s* (*s* = 1, 2, 3 ...S).

4.2.1 The Segment-Specific AV Adoption Choice Model Formulation

We assume a random utility framework as the basis for individuals' choice of AV adoption mode. We also assume that the random components in the mode utilities have a normal distribution with a mean vector of zero and covariance matrix Ω and are independent and identically distributed. Let *I* (*I=4*) be the number of alternatives corresponding to the nominal variable and let *i* be the corresponding index (*i* = 1, 2, 3… *I*). Let *Q* be the number of individuals in the sample, and let *q* be the corresponding index (*q* =1, 2…*Q*). Note that *I* is constant across individuals. We use a typical utility maximizing framework, and write the utility for alternative *i* and household *q,* conditional on belonging to segment *s,* as:

$$U_q(i)\,|\,s = U_{qis} = \boldsymbol{\beta}_s'\boldsymbol{x}_{qi} + \varepsilon_{qis}, \tag{1}$$

where $\boldsymbol{x}_{qi}$ is a (*K*×1)-column vector of exogenous attributes, $\boldsymbol{\beta}_s$ is the segment-specific (*K*×1)-column vector of corresponding coefficients, and ε_{qis} is a segment-specific normal scalar error term. Let the variance-covariance matrix of the vertically stacked vector of errors $\boldsymbol{\varepsilon}_{qs} = [(\varepsilon_{q1s},\ \varepsilon_{q2s},\ ...,\ \varepsilon_{qIs})']$ be $\boldsymbol{\Lambda}_s$. The size of $\boldsymbol{\varepsilon}_{qs}$ is $(I\times 1)$, and the size of $\boldsymbol{\Lambda}_s$ is $(I\times I)$. The error vector $\boldsymbol{\varepsilon}_{qs}$ is identically and independently distributed across households. The parameter vector to be estimated in the segment-specific choice model is $\boldsymbol{\theta}_s = (\boldsymbol{\beta}_s'; \overline{\boldsymbol{\Lambda}}_s')'$, where $\overline{\boldsymbol{\Lambda}}_s$ represents the row vectorization of the upper diagonal elements of $\boldsymbol{\Lambda}_s$.

The segment-specific model above may be written in a more compact form by defining the following vectors and matrices: $\boldsymbol{U}_q\,|\,s = \boldsymbol{U}_{qs} = (U_{q1s}, U_{q2s}, ..., U_{qIs})'$ $(I\times 1$ vector), $\boldsymbol{x_q} = (\boldsymbol{x_{q1}}, \boldsymbol{x_{q2}}, \boldsymbol{x_{q3}}, \ldots, \boldsymbol{x_{qI}})'$ $(I\times K$ matrix), and $\boldsymbol{V_{qs}} = \boldsymbol{x_q}\boldsymbol{\beta}_s$ $(I\times 1$ vector). Then, $\boldsymbol{U}_{qs} \sim MVN_I\,(\boldsymbol{V}_{qs}, \boldsymbol{\Lambda}_s)$, where $MVN_I\,(\boldsymbol{V}_{qs}, \boldsymbol{\Lambda}_s)$ is the multivariate normal distribution of I dimensions with mean vector $\boldsymbol{V}_{qs}$ and covariance $\boldsymbol{\Lambda}_s$. Consider now that the respondent *q* chooses alternative m_q. Under the utility maximization paradigm, $U_{qis} - U_{qm_qs}$ must be less than zero for all $i \neq m_q$, since the respondent chose alternative m_q. Let $u_{qim_qs} = U_{qis} - U_{qm_qs} (i \neq m_q)$, and stack the latent utility differentials into an $[(I-1)\times 1]$ vector $\boldsymbol{u}_{qs} = \left[\left(u_{q1m_qs}, u_{q2m_qs}, ..., u_{qIm_qs}\right)'; i \neq m_q\right]$. Then, $\mathbf{u}_{qs} < \mathbf{0}_{I-1}$, conditional on the individual q belonging to segment s.

To develop the segment-specific choice model likelihood function, define $\mathbf{M}_q$ as an identity matrix of size *(I-1)* with an extra column of '-1' values added at the m_q^{th} column (thus, $\mathbf{M}_q$ is a matrix of dimension $[(I-1)\times I]$. Then, $\mathbf{u}_{qs}$ is distributed as follows: $\mathbf{u}_{qs} \sim MVN_H\,(\boldsymbol{B}_{qs}, \boldsymbol{\Xi}_{qs})$, where $\boldsymbol{B}_{qs} = \mathbf{M}_q\mathbf{V}_{qs}$ and $\boldsymbol{\Xi_{qs}} = \mathbf{M}_q\boldsymbol{\Lambda}_s\mathbf{M}_q'$. Let $\boldsymbol{\omega}_{\boldsymbol{\Xi}_{qs}}$ be the diagonal matrix of standard deviations of $\boldsymbol{\Xi}_{qs}$. Using the usual notations as described earlier, the likelihood of individual *q* choosing alternative m_q conditional on belonging to segment *s* is :

$$L_{qs}(\boldsymbol{\theta}_s) = \left[\text{Prob}(q\, chooses\ alt.\ m_q) \mid q \in segment\, s \right] = \Phi_{I-1}(\boldsymbol{\omega}_{\boldsymbol{\Xi}_{qs}}^{-1}(-\boldsymbol{B}_{qs}), \boldsymbol{\Xi}_{qs}{}^{*}),$$ where

$$\boldsymbol{\Xi}_{qs}{}^{*} = \boldsymbol{\omega}_{\boldsymbol{\Xi}_{qs}}^{-1} \boldsymbol{\Xi}_{qs} \boldsymbol{\omega}_{\boldsymbol{\Xi}_{qs}}^{-1}. \tag{2}$$

Of course, after estimation is complete (the estimation approach is discussed later in this section), the analyst can use the equivalent of (2) to compute the expected probability that individual q will choose any alternative i conditional on belonging to segment s (that is, $P_q(i) \mid s$), simply by replacing $\mathbf{M}_q$ above by the matrix $\tilde{\mathbf{M}}_{qi}$ where $\tilde{\mathbf{M}}_{qi}$ is constructed exactly as $\mathbf{M}_q$ except that the extra column of '-1' values is added at the i^{th} column instead of the m_q^{th} column.

In the context of the formulation above, several important identification issues need to be addressed (in addition to the usual identification consideration that one of the alternatives has to be used as the base when introducing alternative-specific constants and variables that do not vary across the I alternatives). First, only the covariance matrix of the error differences is estimable. Taking the difference with respect to the first alternative, only the elements of the covariance matrix $\breve{\boldsymbol{\Lambda}}_s$ of $\breve{\boldsymbol{u}}_{qs} = (U_{q2s} - U_{q1s}, U_{q3s} - U_{q1s}, ..., U_{qIs} - U_{q1s})$ are estimable. Thus, $\boldsymbol{\Lambda}_s$ is constructed from $\breve{\boldsymbol{\Lambda}}_s$ by adding an additional row on top and an additional column to the left. All elements of this additional row and column are filled with values of zeros. Second, an additional scale normalization needs to be imposed on $\breve{\boldsymbol{\Lambda}}_s$. For this, we normalize the first element of $\breve{\boldsymbol{\Lambda}}_s$ to the value of one. Third, in MNP models, identification is tenuous when only respondent-specific covariates are used (see Keane, 1992), as is the case in our empirical application. In particular, exclusion restrictions are needed in the form of at least one respondent characteristic being excluded from each alternative's utility in addition to being excluded from a base alternative (but appearing in some other utilities).

4.2.2 The Segment Membership Model Formulation

The segment membership probability that individual q belongs to segment s is next written as a function of a vector $\boldsymbol{z}_q$ of variables associated with the individual ($\boldsymbol{z}_q$ includes a constant). $\boldsymbol{z}_q$ may include observed exogenous characteristics of the individual and also the expected values of the individual latent psychological constructs originating from the SEM component (in our empirical application, none of the observed exogenous characteristics of the individual turned out to be statistically significant determinants of segment membership, once the latent psychological constructs were introduced in the segment membership model; that is, the effects of the observed exogenous characteristics on segment membership are all channeled indirectly through the latent psychological constructs rather directly). Using a multinomial logit formulation, the segment membership probability can be expressed as:

$$P_{qs} = \frac{e^{\boldsymbol{\gamma}_s' \boldsymbol{z}_q}}{\sum_{s=1}^{S} e^{\boldsymbol{\gamma}_s' \boldsymbol{z}_q}}, \tag{3}$$

where $\boldsymbol{\gamma}_s$ is a vector of coefficients, with all elements of $\boldsymbol{\gamma}_1$ normalized to zero for identification. The approach to estimate $\boldsymbol{\gamma}_s$ (s=1,2,…S) is discussed later. But once the $\boldsymbol{\gamma}_s$ vectors are estimated, the expected probability that an individual q belongs to segment s is based on equation (3) after replacing the $\boldsymbol{\gamma}_s$ vectors with their estimated counterparts. The expected size of each segment (in terms of share), R_s, may be obtained as:

$$R_s = \frac{\sum_q P_{qs}}{Q} \tag{4}$$

where Q is the total number of individuals in the estimation sample. The values of the $\boldsymbol{z}_q$ vector elements that characterize each segment can be inferred from the signs of the coefficients in equation (2). A more intuitive way is to estimate the means of the $\boldsymbol{z}_q$ vector elements in each segment as follows (Bhat, 1997):

$$\overline{\boldsymbol{z}}_s = \frac{\sum_q P_{qs}\boldsymbol{z}_q}{\sum_q P_{qs}}. \tag{5}$$

However, in our empirical case, $\boldsymbol{z}_q$ contains only the expected values of the latent psychological constructs in the final segment membership model specification impacting P_{qs}. To better trace segment membership to observed exogenous individual-level variables (for policy insights), a simple way is to identify all the distinct (unique) observed exogenous variables impacting the three latent psychological constructs (as obtained from the GHDM model) and collect them in an exogenous variable vector $\boldsymbol{w}_q$ for each individual. Then, since the effects of the elements of $\boldsymbol{w}_q$ on segment membership is already captured through P_{qs}, one can use the equivalent of Equation (5) to determine the means of the $\boldsymbol{w}_q$ vector elements in each segment. However, since all the demographic variables appear in categorical form in our final specification (alternative functional forms, including a continuous functional form and a piece-wise linear form were considered for variables such as age and income, but the categorical form came out to be the best in our final specification), we customize the equivalent of Equation (5) by converting the categorical representation of a variable into a series of dummy variables. For example, age appears in four categories in the final specification: Age (≥55 years) being the base category, Age 18-34 years (say the AGE0 category for ease in presentation), Age 35-44 years (AGE1 category), and Age 45-54 years (AGE2 category). For the age variable, then, we develop dummy (0-1) variables for each of these categories for each individual. Let these be represented by $DAGE1_q, DAGE2_q,$ *and* $DAGE3_q$, respectively. Then, we use these dummy variables to obtain the mean fractions of individuals of each group within each segment:

$$FAGE1 = \frac{\sum_q P_{qs} DAGE1_q}{\sum_q P_{qs}}, FAGE2 = \frac{\sum_q P_{qs} DAGE2_q}{\sum_q P_{qs}}, FAGE3 = \frac{\sum_q P_{qs} DAGE3_q}{\sum_q P_{qs}} \text{, and} \tag{6}$$

$$FAGE0 = 1 - FAGE1 - FAGE2 - FAGE3.$$

4.2.3 Overall Latent Segment Model Formulation

The unconditional (on segment membership) probability of individual q choosing the observed chosen AV adoption alternative m_q (that is, the overall likelihood function) can be written from equations (2) and (3) as:

$$L_q(\boldsymbol{\theta}) = \sum_{s=1}^{S} P_{qs} \times L_{qs}(\boldsymbol{\theta}_s),\ \boldsymbol{\theta} = (\boldsymbol{\theta}_1, \boldsymbol{\theta}_2, ..., \boldsymbol{\theta}_S)', \tag{7}$$

and the log-likelihood function to be maximized is $\sum_{q=1}^{Q} \ln L_q(\boldsymbol{\theta})$.

A couple of points are in order here. First, in estimating the latent segment model, labeling restrictions are needed for identifiability. To prevent the interchange of the mixture components, we impose the labeling restriction that the constants specific to the second alternative are increasing across the segments. Such a labeling restriction is needed because the same model specification (and likelihood function value) results simply by interchanging the sequence in which the segments are numbered. Technically, therefore, multiple sets of parameters (corresponding to a swap of segment values) result in the same likelihood function, creating an identification problem. This identification problem is resolved through the imposition of the labeling restriction above so that the segments become non-interchangeable. Of course, other labeling restrictions are also possible (see Bhat *et.al.*, 2016). Second, we use a two-step procedure in which the latent variables are estimated in a prior GHDM step, and their expected values are used in the second latent segment model. We do so because a joint estimation of both these steps can be computationally unstable in the presence of mixture distributions. However, the two-step approach also implies that the standard errors from the second step will be generally under-estimated. To correct for this, we use the procedure suggested by Murphy and Topel (2002).

Once estimated, the model can be used to predict the choice of AV adoption at the individual level and segment level. The individual-level choice probabilities can be obtained as $P_q(i) = \sum_{s=1}^{S} P_{qs} \times [P_q(i) \mid s]$. The segment-level AV adoption shares can be obtained as:

$$G_s(i) = \frac{\sum_q P_{qs} \times [P_q(i) \mid s]}{\sum_q P_{qs}}. \tag{8}$$

5. RESULTS

The choice models for the two segments are estimated jointly, and the results of the SEM portion of the model are provided in Table 2:

- Tech Savvy latent construct:
    - Younger the individual, higher the probability of tech-savviness, base being age more than 55 years of age.
    - Part time employees have a lesser probability of being tech-savvy, as compared to full-time or self-employed individuals
    - As income increases, the probability to be a part of this group increases.
- Variety-seeking latent construct:
    - Males have a higher probability to have variety seeking nature, as compared to females.
    - People with age 18 to 34 years of age and those of 35 to 44 years have a higher probability too, as compared to all greater in age.
    - Non-Hispanic white individuals have a lesser probability, as compared to all other races.
    - Multi person household with a single worker has a lower probability to be a part of this group, base case being single person and multi worker households.
    - Income of more than $200,000 gives a higher probability for the individual to be a part of this group
- Time sensitivity latent construct:
    - Females have a higher probability to be a part of this group, as compared to males.
    - People with age 35 to 44 years have a higher probability to be a part of this group, as compared to those greater than 55 years of age.
    - Part time employees have a lesser chance of being in this group, as compared to full-time or self-employed individuals

These three latent constructs are used to develop two latent segments, each of which examines the choice making process conditional on these latent constructs. The choice among the alternative sot adopt and willingness to pay for AVs were examined for the two segments simultaneously. The results of the model estimation are given in Table 3. The two segments based on latent constructs are examined in detail to understand how the behavior of individuals varies within these segments and what socio-demographic characteristics drive this difference in segments. The segmentation model estimates suggest that segment 2 has a lower estimate of tech savviness and variety seeking nature, while it has a higher estimate of time sensitivity. This characterizes group 1 as the *Tech-savvy and Variety seeking Group* and group 2 as the *Time-sensitive Group*.

Within the segments, we observe:
Tech-savvy and Variety seeking Group

- Higher the perception of safety, higher is the WTP for AVs. The willingness to pay $5,000 more than the price of regular vehicle is higher than the willingness to pay more than $5,000, conditional on a higher perception of safety.
- Higher the appeal of AVs to inspire productive use of travel time, higher is the WTP for AVs. The willingness to pay more than $5,000 greater than the price of regular vehicle is higher than the willingness to pay $5,000 above the price of a regular vehicle, conditional on a higher perception of productive use of travel time.
- Owning a vehicle with more than three automated features increases the WTP for AVs, particularly willingness to pay an amount higher than $5,000 than the price of a regular vehicle.

The appeal of self-driving cars towards productive use of travel time increases the willingness to pay a high premium for an AV. Similarly, the safety perception plays an important role in the adoption of AVs but the willingness to pay a premium is more likely to be capped at $5,000. Owning a vehicle with automated features also contributes to owning a fully autonomous vehicle in the future. The individuals who contribute towards these results are primarily males, 35 to 54 years of age who have obtained an undergraduate degree or higher, part of a multi worker household and are non-Hispanic Caucasians. They have a full-time employment with an income of $50,000 to $150,000. It can be argued that these characteristics play a major role in paying a price premium of $5,000 or more towards a new AV vehicle. The individuals belonging to this *tech-savvy* segment are not only willing to adopt but also pay a higher price for an AV.

Time-sensitive Group

- Higher the perception of safety, higher is the overall intention to adopt AVs, but no distinction in WTP for various automation levels
- Higher the appeal of AVs to inspire productive use of travel time, higher is the overall intention to adopt AVs, but no distinction in WTP for various automation levels

The appeal of productive use of travel time and safety perception increases the willingness to adopt AVs without an intention to pay any premium for the technology. The individuals who contribute towards these results are primarily aged 45 and above, who have obtained an undergraduate degree or higher, being part of a multi worker household and are non-Hispanic Caucasians. They have a higher propensity of a full-time employment with an income of $50,000 to $150,000. These characteristics of individuals within this segment. It can be argued that these characteristics play a major role in paying either no extra money or only a price premium of $5,000 or less towards a new AV vehicle. The individuals belonging to this *time-sensitive* segment are only willing to adopt an AV at the same price or a minimum premium over the price of a regular vehicle.

To isolate the effects of the latent constructs on each of these groups, the estimate the mean of the latent constructs in each segment is calculated using segment probabilities and the expected values of latent constructs, as given in equation (5). For the first segment, the mean of the expected values of tech savviness and variety seeking are higher than the full sample mean values respectively, while the mean value of time-sensitivity is lower than the sample mean of time sensitivity. Similarly, for the second segment, the mean of the expected value of time sensitivity is higher than the full sample mean of time sensitivity, while the mean values of tech savviness and variety seeking are lower than the respective sample means. These values reinforce the segmentation model results for both the segments.

Using equations 2, 3, 4, 5 and 8, we can calculate the segment specific share of alternatives, based on the choices made by the individuals characterized as either tech-savvy or time-sensitive (equation (8)). Finally, the size of each segment (in terms of share) which could be obtained using equation (4) in the methodology. The results call for a better understanding on how the effects of variables, which constitute the latent constructs, permeate into the choice process. To trace segment membership to observed exogenous individual-level variables, the fractions of all the distinct exogenous variables were calculated for each of the segments (and compared with the full sample fractions for policy analysis):

Covariance between the alternatives:
Given that the alternatives of the outcome variable may seem highly correlated, an attempt was made to estimate the covariance matrix. As given in methodology, the usual identification consideration dictates that one of the alternatives has to be used as the base when introducing alternative-specific constants and variables that do not vary across the *I* alternatives. Therefore, only the covariance matrix of the error differences is estimable. Various specifications were tried by the authors, but they were all insignificant. The above-mentioned results, thus, conclude from an IID specification on the covariance matrix.

Scale Effects:
For the availability of scaled differential across segments, the methodology assumed same covariance matrix across segments, but with different scaling coefficients. However, introducing a scaled differential turned out to be insignificant.

6. GOODNESS OF FIT STATISTICS

As provided in the table 5, the log-likelihood at convergence shows that the two-segment model is better than the MNP model. Similar conclusion can be made using the results from predictive log-likelihood ratio index calculation. To test the performance of two non-nested models, the non-nested adjusted likelihood ratio test may be used (see Ben-Akiva and Lerman, 1985, page 172). This test determines if the adjusted likelihood ratio indices of two non-nested models are significantly different. A small value of the probability of chance occurrence indicates that the difference is statistically significant and that the model with the higher value of adjusted likelihood ratio index is to be preferred, which in this case is the latent-class latent-variable model. The probability that the adjusted likelihood ratio index difference between two models could have occurred by chance is literally zero. To get a better understanding of predictive accuracy of the latent-class model as compared to the MNP model, we also calculate the predicted shares of alternatives for each model. We also provide the comparison of the predicted share of alternative by the Latent-Class and MNP models, and the comparison of the absolute percentage errors of each alternative for Latent-Class and MNP models. Both these comparisons show that for each alternative how is the latent-class model different from the MNP model.

7. CONCLUSIONS

Introduction of AVs bring along a promise of reduction in crashes, costs of congestion, energy consumption, and pollution. Yet, there is an apparent disparity between the automotive industry's expectation of AV demand and consumer's perspectives on AV benefits. Therefore, it is an immediate necessity to understand what factors drive a user towards adoption of AV technology. The recent attention given to safety perspectives and time-use benefits suggest the feasibility of these factors affecting consumer's adoption decision. In this study, we undertook a comprehensive analysis of willingness to adopt and pay for AV by developing a latent-segmentation model with latent variables, such as tech-savviness, time-sensitivity and variety seeking propensity, defining the segments and opinion variables, such as perception of productive use of travel time in AVs and perception of safety in AVs, defining segment specific choice. This analysis serves to identify the segment of the population which is more likely to adopt and pay a premium for an AV. This is the segment who might be more aware of the environmental benefits, travel-time savings and other potential AV benefits.

Our results show that the appeal of autonomous vehicles, to consumers who are willing to pay more, is deriving its utility from perceptions of a higher propensity to use one's travel time productively by engaging in activities while commuting, as well as, from the perceptions of higher safety provided by these technologies. The segmentation results suggest that is important to study the effect of latent constructs as they isolate the individuals who're more tech-savvy and seek variety in their life for the adoption of AVs. However, these individuals still form a segment share of 55%, while the rest of the population is unwilling to pay a premium. In addition to above, existing exposure to semi-autonomous technologies provide the propensity to adopt fully autonomous vehicles.

Generally, this study unravels the underlying behaviors which motivate individuals towards adoption of new technologies. AVs can provide the user with higher safety the ability to use his/her travel time more effectively, given that the buyer is well-informed of the potential benefits and is willing to purchase his/her next car with fully autonomous capabilities. On a more individual front, people of both very high and extremely low mobility can employ AVs in various ways. For those with high mobility, AVs can provide travel time savings which can be utilized for tasks such as working. For those with reduced mobility, AVs can provide a mode of transportation where the individual does not have to drive the car. One of the major limitations of this type of analysis is the lack of availability of a realistic adoption costs in the current car-market. Also, there is no evidence of awareness in the general public about the general structure of AV technology. Awareness of AV technology and its potential benefits can provide a fast-track pathway to a future towards higher vehicular safety.

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8. REFERENCES

1. Abraham, H., Reimer, B., Seppelt, B., Fitzgerald, C., Mehler, B. and Coughlin, F., 2017. Consumer Interest in Automation: Preliminary Observations Exploring a Year's Change. MIT Angel Lab, White Paper (2017-2). http://agelab.mit.edu/sites/default/files/MIT%20-%20NEMPA%20White%20Paper%20FINAL.pdf. Accessed October 12, 2017.
2. Alemi, F., Circella, G., Handy, S., Mokhtarian, P., 2017. What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services. Presented at the 96th Annual Meeting of the Transportation Research Board, Washington, D.C., January, Paper No. 17-05630.
3. Bansal, P., and Kockelman, K. (2015) Forecasting Americans' Long-Term Adoption of Connected and Autonomous Vehicle Technologies. Under review for presentation at the 95th Annual Meeting of Transportation Research Board and for publication in Transportation Research Part A. Retrieved from: http://www.caee.utexas.edu/prof/kockelman/public_html/TRB16CAVTechAdoption.pdf (September 4, 2015).
4. Bansal, P., Kockelman, K., Singh, A. (2016) Assessing public opinions of an interest in new vehicle technologies: an Austin perspective. *Transportation Research C.*
5. Becker, F., Axhausen, K.W., 2017. Literature review on surveys investigating the acceptance of autonomous vehicles, paper presented at the 96th Annual Meeting of the Transportation Research Board, Washington, D.C., January 2017. <https://www.ethz.ch/content/dam/ethz/special-interest/baug/ivt/ivt-dam/vpl/reports/1101-1200/ab1179.pdf >.Publisher IVT ETH Zürich.
6. Ben-Akiva, M.E., and Lerman, S.R., 1985. Discrete Choice Analysis: Theory and application to travel demand (Vol. 9). The MIT Press, Cambridge, MA.

7. Bhat, C.R. (2011), "The Maximum Approximate Composite Marginal Likelihood (MACML) Estimation of Multinomial Probit-Based Unordered Response Choice Models," Transportation Research Part B, Vol. 45, No. 7, pp. 923-939
8. Bhat, C.R. (2015), "A New Generalized Heterogeneous Data Model (GHDM) to Jointly Model Mixed Types of Dependent Variables," Transportation Research Part B, Vol. 79, pp. 50-77
9. Bhat, C. R. An Endogenous Segmentation Mode Choice Model with an Application to Intercity Travel. *Transportation Science*, Vol. 31, No. 1, 1997, pp. 34–48.
10. Bhat, C.R., S. Astroza, and A.C. Bhat (2016), "On Allowing a General Form for Unobserved Heterogeneity in the Multiple Discrete-Continuous Probit Model: Formulation and Application to Tourism Travel," Transportation Research Part B, Vol. 86, pp. 223-249
11. Cambridge Systematics, 2011. Crashes vs. Congestion: What's the Cost to Society? Prepared for the American Automobile Association. <http://www.camsys.com/pubs/2011_AAA_CrashvCongUpd.pdf> (March 6, 2015).
12. Daziano, R.A., M.A. Sarrias and B. Leard. 2017. Are consumers willing to pay to let cars drive for them? Analyzing response to autonomous vehicles. Transportation Research Part C: Emerging Technologies 78, 150-164
13. Deloitte, 2017. Deloitte Study: Fact, Fiction and Fear Cloud Future of Autonomous Vehicles in the Mind of Consumers. https://www2.deloitte.com/us/en/pages/about-deloitte/articles/press-releases/deloitte-study-future-of-autonomous-vehicles-in-minds-of-consumers.html. Accessed October 12, 2017.
14. Haboucha C. J., R. Ishaq, Y. Shiftan. User preferences regarding autonomous vehicles. Transportation Research Part C: Emerging Technologies, Volume 78, 2017, 37-49.
15. Häne, C., Sattler, T., Pollefeys, M., 2015. Obstacle detection for self-driving cars using only monocular cameras and wheel odometry. In: Intelligent Robots and Systems (IROS), 2015 IEEE/RSJ International Conference on. IEEE, pp. 5101–5108.
16. Harper, C.D., Hendrickson, C.T., Mangones, S., Samaras, C., 2016. Estimating potential increases in travel with autonomous vehicles for the non-driving, elderly and people with travel-restrictive medical conditions. Transp. Res. Part C: Emerg. Technol. 72, 1–9.
17. J. D. Power, 2017. Hands Off? Not Quite. Consumers Fear Technology Failures with Autonomous Vehicles. https://www.prnewswire.com/news-releases/hands-off-not-quite-consumers-fear-technology-failures-with-autonomous-vehicles-300441106.html. Accessed October 12, 2017.
18. Keen, A., 2013. The Future of Travel: How Driverless Cars Could Change Everything. <http://www.cnn.com/2013/05/14/business/bussiness-travellerfuturecast-driverless-car/> (11 August, 2017)
19. Kovacs, P., 2016. Automated Vehicles: Implications for the Insurance Industry of Canada. The Insurance Institute of Canada: Toronto, ON.
20. Krueger, R., Rashidi, T.H., Rose, J.M.: Preferences for shared autonomous vehicles. Transp. Res. C 69, 343–355 (2016)
21. Kyriakidis, M., Happee, R., de Winter, J., 2015. Public opinion on automated driving: results of an international questionnaire among 5000 respondents. Transp. Res. Part F 32, 127–140.
22. Lavieri, P.S., V.M. Garikapati, C.R. Bhat, R.M. Pendyala, S. Astroza, and F.F. Dias (2017), "Modeling Individual Preferences for Ownership and Sharing of Autonomous Vehicle Technologies," Transportation Research Record, Vol. 2665, pp. 1-10
23. Levinson, J., Askeland, J., Becker, J., Dolson, J., Held, D., Kammel, S., Kolter, J.Z., Langer, D., Pink, O., Pratt, V., Sokolsky, M., 2011. Towards fully autonomous driving: systems and algorithms. In: Intelligent Vehicles Symposium (IV), 2011 IEEE. IEEE, pp. 163–168.
24. Litman, T., 2015. Autonomous Vehicle Implementation Predictions: Implications for Transport Planning. <www.vtpi.org/avip.pdf> (11 August, 2017).
25. Merat, N., Lee, J.D., 2012. Preface to the special section on human factors and automation in vehicles: designing highly automated vehicles with the driver in mind. Hum. Fact. 54 (5), 681–686.

26. Mersky, A.C., Samaras, C., 2016. Fuel economy testing of autonomous vehicles. Transp. Res. Part C: Emerg. Technol. 65, 31–48.
27. Murphy, Kevin and Topel, Robert, (2002), Estimation and Inference in Two-Step Econometric Models, Journal of Business & Economic Statistics, 20, issue 1, p. 88-97, https://EconPapers.repec.org/RePEc:bes:jnlbes:v:20:y:2002:i:1:p:88-97.
28. NHTSA (National Highway Traffic Safety Administration), 2008. National Motor Vehicle Crash Causation Survey. U.S. Department of Transportation, Report DOT HS 811 059. <http://www-nrd.nhtsa.dot.gov/Pubs/811059.PDF> (October 15, 2014).
29. NHTSA (National Highway Traffic Safety Administration), 2014. 2013 Motor Vehicle Crashes: Overview. <http://www-nrd.nhtsa.dot.gov/Pubs/812101. pdf> (March 26, 2015).
30. Nordhoff, S., van Arem, B., Happee, R., 2016. Conceptual model to explain, predict, and improve user acceptance of driverless Podlike vehicles. Transp. Res.Rec.: J. Transp. Res. Board 2602, 60–67.
31. Rieser-Schüssler, N., Axhausen, K., 2012. Investigating the influence of environmentalism and variety seeking on mode choice. Transportation Research Record: Journal of the Transportation Research Board 2322, 31-41.
32. Robertson, R.D., Vanlaar, W.G.M., Marcoux, K., McAteer, H.J., 2012. Vehicle Safety Features: Knowledge, Perceptions, and Driving Habits. Traffic Injury Research Foundation (TIRF), Ottawa, ON.
33. Rudin-Brown, C., Burns, P., Jenkins, R., Whitehead, T., LeBlond, O., 2011. ESC (Electronic Stability Control) Public and Driver Surveys. Transport Canada: TP 14848E.
34. Schoettle, B., Sivak, M., 2014. Public Opinion About Self-Driving Vehicles in China, India, Japan, the U.S., the U.K., and Australia. University of Michigan Transportation Research Institute, pp. 1–31.
35. Singleton, Patrick A., 2018. Discussing the “positive utilities” of autonomous vehicles: will travellers really use their time productively? Transport reviews, 0144-1647
36. Silberg, G., Wallace R., and G. Matuszak. Self-driving cars: The next revolution. 485 KPMG and Center for Automotive Research, 2012.
37. Tudela, A., Habib, K.M.N., Carrasco, J.A., Osman, A.O., 2011. Incorporating the explicit role of psychological factors on mode choice: A hybrid mode choice model by using data from an innovative psychometric survey. Presented at 2nd International Choice Modelling Conference, Leeds.
38. Underwood, S.E., 2014. Automated vehicles forecast vehicle symposium opinion survey. Presentation at the 2014 Automated Vehicles Symposium, San Francisco, CA, pp. 15–17.
39. U.S. Census Bureau, 2018a. New Census Bureau Population Estimates Show Dallas-Fort WorthArlington Has Largest Growth in the United States. Release Number: CB18-50. Available at: https://www.census.gov/newsroom/press-releases/2018/popest-metro-county.html [Accessed: 06/23/2018].

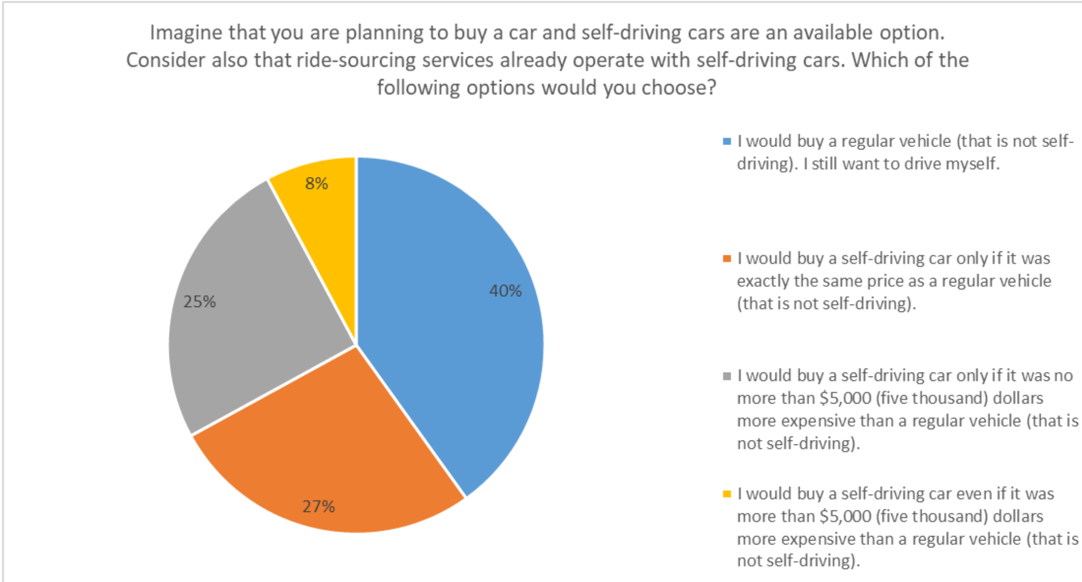

Figure 1. Sample distribution of outcome variable

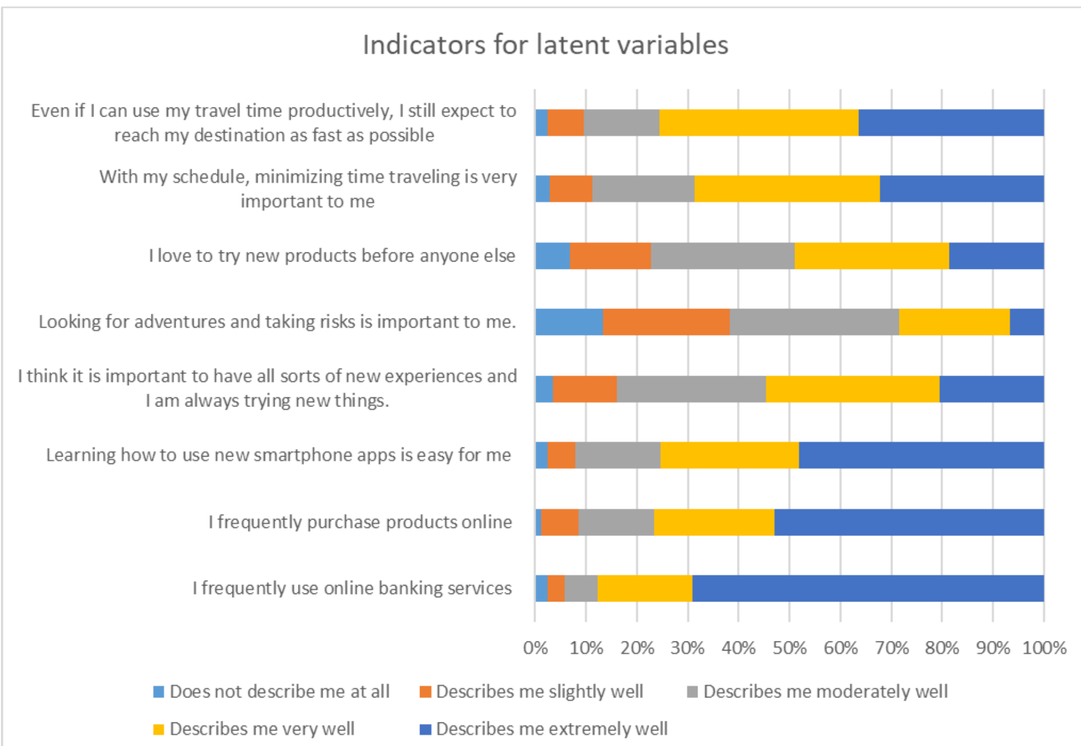

Figure 2. Sample distribution of attitudinal/behavioral indicators

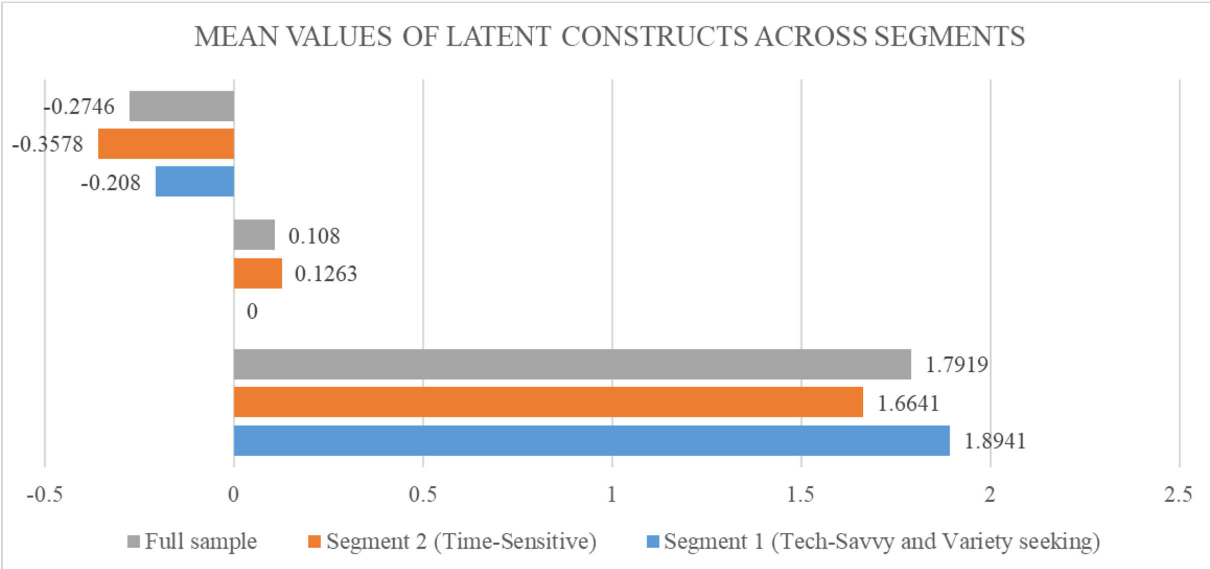

Figure 3. Comparison of mean values of latent constructs across segments with the sample mean

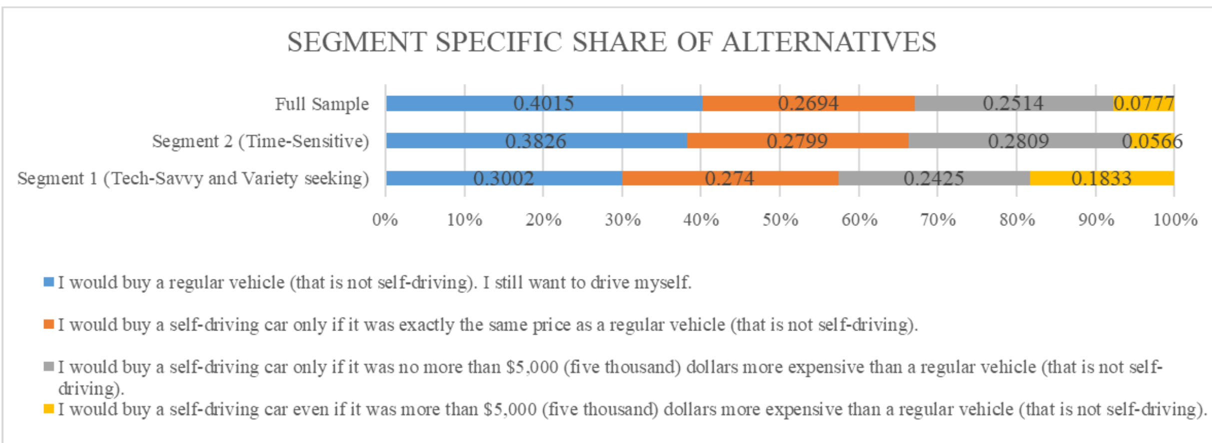

Figure 4. Comparison of segment-specific share of alternative with the sample share

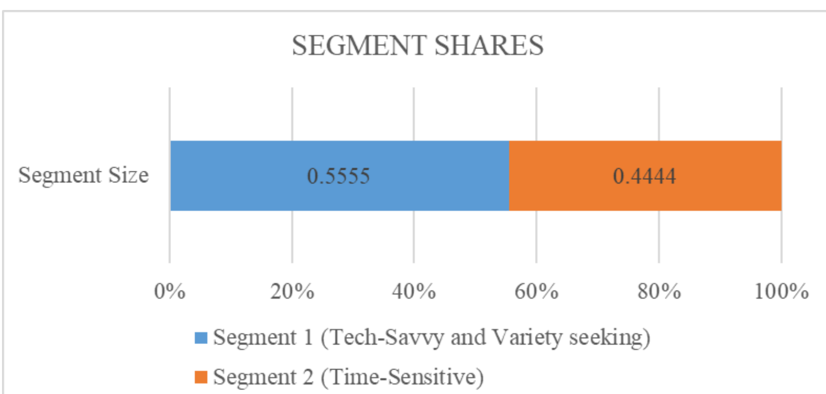

Figure 5. Sample share of the two segments

Table 1. Sample distribution of socio-demographic characteristics

Variable	Count	%
Gender		
Female	645	41.37%
Male	914	58.62%
Age		
18 to 34	256	16.42%
35 to 44	351	22.51%
45 to 54	417	26.74%
55 to 64	406	26.04%
65 or more	129	8.27%
Race		
Non-Hispanic White	1,171	75.11%
Non-Hispanic Black	98	6.28%
Hispanic	104	6.67%
Asian/Pacific Islander	101	6.47%
Other	85	5.45%
Education		
Completed high-school	231	14.81%
Completed technical school/associates degree	148	9.49%
Completed undergraduate degree	706	45.28%
Completed graduate degree	474	30.40%
Student (attending institution in person)		
Yes	134	8.88%
No	1,375	91.11%
Employment type		
Full-time employee	1,273	81.65%
Part-time employee	134	8.59%
Self-employed	152	9.74%
Household income		
Under $49,999	179	11.48%
$50,000-$99,999	424	27.19%
$100,000-$149,999	487	31.23%
$150,000-$199,999	261	16.74%
$200,000 or more	208	13.34%
Household composition		
Single person household	186	11.93%
Single worker multi-person household	255	16.35%
Multi-worker household	1,118	71.71%

Table 2 Structural Equations Model component results

Variables (base category)	Tech-savviness		Time-sensitivity		Variety-Seeking	
	Coeff.	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
Gender (male)						
Female	--	--	0.1888	2.79	-0.2221	-3.69
Age (≥55 years)						
18 to 34	1.0983	10.79	--	--	0.4318	5.16
35 to 44	0.8848	9.91	0.2826	3.52	0.2467	3.42
45 to 54	0.4517	5.56	--	--	--	--
Race (other races)						
Non-Hispanic White	--	--	--	--	-0.1852	-2.54
Employment (full-time or self-employed)						
Part-time employee	-0.3991	-3.46	-0.3925	-3.27	--	--
Household income (< $50,000)						
$50,000-$99,999	0.2595	2.15	--	--	--	--
$100,000-$149,999	0.4003	3.35	--	--	--	--
$150,000-$199,999	0.6304	4.75	--	--	--	--
$200,000 or more	0.8000	5.64	--	--	0.2489	2.88
Household composition (single person and multi-worker)						
Single worker multi-person	--	--	--	--	-0.2022	-2.45
Correlations between latent variables						
Tech-savviness	1.0000	n/a				
Time-sensitivity	0.1790	4.03	1.0000	n/a		
Variety-Seeking	0.4060	11.16	0.1030	2.56	1.0000	n/a

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

Table 3. Latent-class and latent-variable model results

SEGMENTATION MODEL

Variable	Segment 1 (Tech-Savvy and Variety seeking)		Segment 2 (Time-Sensitive)	
	Coeff.	t-stat	Coeff.	t-stat
Constant	Base Segment		0.6386	1.02
Tech Savviness			-0.9835	-2.88
Time-Sensitivity			0.4890	1.69
Variety seeking			-2.8988	-3.47

SEGMENT SPECIFIC CHOICE MODEL

Variable	Segment 1 (Tech-Savvy)							
	I would buy a regular vehicle (that is not self-driving). I still want to drive myself.		I would buy a self-driving car only if it was exactly the same price as a regular vehicle (that is not self-driving).		I would buy a self-driving car only if it was no more than $5,000 (five thousand) dollars more expensive than a regular vehicle (that is not self-driving).		I would buy a self-driving car even if it was more than $5,000 (five thousand) dollars more expensive than a regular vehicle (that is not self-driving).	
	Coeff.	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
Alternative Constants	Base Case		-0.4055	-2.99	-0.9951	-5.52	-1.5149	-8.36
Self-driving vehicles are appealing because they will allow me to use my travel time more effectively			0.6373	2.16	1.1471	4.22	1.5911	5.70
I believe I would be safe from crashes in a self-driving vehicle			0.8300	2.87	1.4939	3.46	1.2915	3.49
Three or more automated features in current vehicle			-	-	-	-	0.3305	2.34

Variable	Segment 2 (Time-Sensitive)							
	I would buy a regular vehicle (that is not self-driving). I still want to drive myself.		I would buy a self-driving car only if it was exactly the same price as a regular vehicle (that is not self-driving).		I would buy a self-driving car only if it was no more than $5,000 (five thousand) dollars more expensive than a regular vehicle (that is not self-driving).		I would buy a self-driving car even if it was more than $5,000 (five thousand) dollars more expensive than a regular vehicle (that is not self-driving).	
	Coeff.	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
Alternative Constants	Base Case		-0.7506	-5.18	-0.7471	-5.62	-1.9106	-3.51
Self-driving vehicles are appealing because they will allow me to use my travel time more effectively			1.1734	5.23	1.1734	5.23	-	-
I believe I would be safe from crashes in a self-driving vehicle			0.4433	2.00	0.4433	2.00	-	-

Table 4. Fractions of socio-demographic characteristics across segments

	Segment 1 (Tech-Savvy and Variety seeking)	**Segment 2 (Time-Sensitive)**	**Full Sample**
Age			
18 to 34	0.1350	0.2000	0.1642
35 to 44	0.3090	0.1203	0.2251
45 to 54	0.2716	0.2622	0.2674
55 and above	0.2844	0.4175	0.3433
Gender			
Female	0.3395	0.5057	0.4137
Male	0.6605	0.4943	0.5863
Education			
Completed high-school	0.1354	0.1641	0.1481
Completed technical school/associates degree	0.0878	0.1038	0.0949
Completed undergraduate degree	0.4556	0.4493	0.4528
Completed graduate degree	0.3212	0.2828	0.3042
Household Structure			
Single person household	0.0973	0.1461	0.1193
Single worker multi-person household	0.1608	0.1669	0.1635
Multi-worker household	0.7419	0.6870	0.7172
Race			
Non-Hispanic White	0.7083	0.8046	0.7511
Non-Hispanic Black	0.0690	0.0544	0.0628
Hispanic	0.0782	0.0523	0.0667
Asian/Pacific Islander	0.0818	0.0433	0.0647
Other	0.0627	0.0454	0.0547
Employment			
Full-time employee	0.8022	0.8344	0.8165
Part-time employee	0.1073	0.0585	0.0859
Self-employed	0.0905	0.1071	0.0976
Income			
Under $49,999	0.0930	0.1413	0.1148
$50,000-$99,999	0.2469	0.3032	0.2719
$100,000-$149,999	0.2977	0.3306	0.3123
$150,000-$199,999	0.1794	0.1523	0.1674
$200,000 or more	0.1830	0.0726	0.1336

Table 5. Disaggregate measures of fit

Summary Statistics	Model: Latent class model	Model: MNP model	
Average probability of correct prediction	0.3375	0.3205	
Log likelihood at convergence	-1683.72	-1705.71	
Log likelihood with only constants	-1941.31		
Number of parameters	19	17	
Predictive adjusted likelihood ratio index	0.1648	0.1142	
Mean absolute percentage error	21.32%	24.50%	
Non-nested adjusted likelihood ratio test	Φ [-11.71] << 0.0001		
Absolute Percentage errors of each alternative			
	Latent class model	**MNP model**	
I would buy a regular vehicle (that is not self-driving). I still want to drive myself.	16.11%	16.86%	
I would buy a self-driving car only if it was exactly the same price as a regular vehicle (that is not self-driving).	2.63%	1.18%	
I would buy a self-driving car only if it was no more than $5,000 (five thousand) dollars more expensive than a regular vehicle (that is not self-driving).	3.22%	1.19%	
I would buy a self-driving car even if it was more than $5,000 (five thousand) dollars more expensive than a regular vehicle (that is not self-driving).	63.32%	78.76%	
Predicted shares of alternatives			
	Latent class model	**MNP model**	**Full Sample**
I would buy a regular vehicle (that is not self-driving). I still want to drive myself.	0.3368	0.3338	0.4015
I would buy a self-driving car only if it was exactly the same price as a regular vehicle (that is not self-driving).	0.2765	0.2726	0.2694
I would buy a self-driving car only if it was no more than $5,000 (five thousand) dollars more expensive than a regular vehicle (that is not self-driving).	0.2595	0.2544	0.2514
I would buy a self-driving car even if it was more than $5,000 (five thousand) dollars more expensive than a regular vehicle (that is not self-driving).	0.1269	0.1389	0.0777