

Sharing the Road with Autonomous Vehicles: Perceived Safety and Regulatory Preferences

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ABSTRACT

Technology providers, car manufacturers, and public agencies all need to work together to undertake extensive testing of fully autonomous vehicles (AVs) on public roads before such AVs are allowed to freely travel in ways similar to human-driven vehicles. This raises the importance of understanding public perceptions regarding safety considerations when traveling alongside AVs. This study makes use of a national survey conducted by the Pew Research Center to identify the affective, socio-demographic and technology-use attributes that affect an individual's perception of the safety of sharing the road with AVs (PSSRAV) and identifies measures and interventions that can be undertaken to improve PSSRAV. Additionally, we evaluate individual preferences for AV regulations. Our results underscore the importance of the need for service providers and public agencies to be cognizant of the demographic and lifestyle/affective emotion considerations shaping AV safety perceptions and opinions about AV regulations. In particular, there is a need not only to focus on technological and other infrastructure components of AV development, but also to recognize the socio-technical considerations and human-related factors of the end-users. Our findings should be of substantial interest in the planning, design, deployment, and introduction of AVs within a safe and minimally regulated public operating arena.

Keywords: autonomous vehicles, driverless cars, safety, regulation, generalized heterogeneous data model, digital assistants

1 INTRODUCTION

The advent of autonomous vehicles (AVs) (sometimes referred to as driverless cars) with no need for human assistance is expected to bring forth a multitude of benefits to the transportation system. AVs can improve mobility by providing last-mile connectivity to transit services (Moorthy et al., 2017; Ohnemus and Perl, 2016) and by being an accessible private transport mode to demographic groups that are unable to drive, including children, differently-abled individuals and others who do not have a driver's license (Harper et al., 2016; Truong et al., 2017). These vehicles may be summoned to a location when needed and dismissed on reaching the destination, which facilitates the sharing of these vehicles and ameliorates parking concerns (Kondor et al., 2018; Zhang et al., 2015). AVs also have the potential to improve the efficiency of the transportation system; since AVs can perceive and react to the environment much faster than humans, they should be able to maintain smaller headways with the vehicle in front, thus increasing the traffic capacity of roads (Shi and Prevedouros, 2016; Tientrakool et al., 2011). Perhaps, the most significant benefit of AV technology will be its impact on traffic safety. In just the year 2018, traffic accidents were responsible for 36,560 deaths in the United States (NHTSA, 2019) and such accidents remain the leading cause of death worldwide of people aged 5-29 years (WHO, 2018). USDOT (2018) estimates that 94% of all serious motor-vehicle crashes involve factors related to human error such as impaired driving, distraction, and speeding or illegal maneuvers. Thus, by eliminating the human driver, AVs can be expected to substantially improve safety.

However, before AVs can be made available for widespread use, it is necessary to demonstrate to the general public as well as regulators that the autonomous driving technology in AVs is mature enough to be at least as safe as human drivers (and perhaps much more). Extensive testing on public roads would be required for AVs to achieve and demonstrate this level of safety. Testing AVs on public roads exposes them to more edge cases, i.e., situations that are challenging and highly improbable but not impossible. The AVs can “learn” from their experiences with edge cases and improve their autonomous driving capability (Fridman et al., 2017). Also, data regarding the performance of AVs gathered from their operation on public roads can be used to convince regulators and the general public that the technology is ready for widespread deployment.

The prospect of sharing the road with AVs (as companies test and demonstrate their capabilities) creates a concern for public safety. Although regulatory bodies are wary of exposing the public to unproven technology, they understand the necessity of testing AVs on public roads.

As of March, 2020, legislation that allows AVs to be tested on public roads has been passed in 29 states in the U.S. and the District of Columbia (Laukkonen, 2020). In California, a state where the testing of AVs is relatively higher than in other states, more than two million miles were driven autonomously in the year 2018 (CA DMV, 2019). Some companies have started offering limited services using AVs in niche environments such as within university campuses and suburban areas where the risk of serious accidents are less (CNA, 2019; Niedermeyer, 2019). As AVs become more prevalent in the future, it becomes essential to understand the concerns of the public for sharing the road with these vehicles. Companies responsible for testing AVs as well as regulatory authorities risk alienating the public if the AVs that are being tested are perceived to be unsafe. Indeed, a recent fatality that involved an AV raised concerns regarding the propriety of companies testing AVs on public roads (Claybrook and Kildare, 2018; Shepardon, 2019).

The goal of this research paper is to further the understanding of the factors that contribute to the perceived safety of sharing the road with AVs. By developing an econometric model capable of predicting safety concerns at the individual level, we are able to identify the specific attributes that are associated with concerns over AV use. Socio-demographic characteristics are used as explanatory variables, which allow us to isolate the specific demographic groups that are more concerned about the possible adverse impacts of AVs. The model also incorporates certain technology use variables that provide insights on whether an individual's current experience with technology can affect their perception of AVs. Possible endogeneities among the outcome variables are modeled by mediating the effect of socio-demographic variables through stochastic latent constructs that capture an individual's tech-savviness and affective response to AVs. Based on the model results, we propose policy measures that could make individuals more amenable to the testing of AVs on public thoroughways. The study uses data from a national survey on AVs and automation conducted by the Pew Research Center – a non-partisan think tank.

The rest of this paper is organized as follows. Section 2 provides a brief overview of past literature that could be relevant to understanding the perceived safety of sharing the road with AVs. Section 3 describes the dataset that is used for our study. Section 4 develops the methodological framework. Section 5 presents the empirical results. Section 6 discusses the practical implications of our findings. Finally, Section 7 concludes by summarizing important findings and briefly identifying future research directions.

2 LITERATURE SYNTHESIS

Many studies have collected and analyzed the opinions of individuals from the perspective of a potential AV user. On the other hand, there are only a limited number of studies on the acceptance of AVs from the perspective of a person who may not be riding an AV but is sharing the road with AVs. However, many of the factors that contribute to an individual's interest in using AVs would also make them more willing to share the road with AVs (Hulse et al., 2018; Moody et al., 2019). Therefore, in this literature overview, we explore the different characteristics that affect an individual's general tendency to accept AVs in addition to the specific characteristics that affect their opinions on sharing the road with AVs.

2.1 Characteristics Affecting AV Acceptance

2.1.1 Socio-Demographic and Affective Attributes

A vast body of literature has explored the effects of socio-demographic attributes on general attitudes toward AVs. The consensus seems to be that men, young adults, well-educated individuals, and individuals belonging to wealthy households and living in urban areas are more accepting of AVs (Capgemini Research Institute, 2019; Kyriakidis et al., 2015; Lavieri et al., 2017; Zmud and Sener, 2017). More recent works by Hohenberger et al. (2016, 2017) suggest that the differences between socio-demographic groups in their behavior towards AV acceptance (in the context of personal use) may be partly attributed to the differences in the affective reactions of these groups toward AVs. Affective attributes refer to the evoked moods and emotions when confronted with events or objects or technology. Specifically, Hohenberger et al. (2016) find women more likely to experience higher levels of anxiety with respect to AVs and men more likely to experience pleasure, which, in turn, make women less likely to accept AVs. Liu and Xu (2020) and Liu et al. (2019) conducted studies to understand the effect of affective reactions and attitudes on AV acceptance in the context of sharing the road with AVs. The authors find that affective attributes do have a substantial impact on the acceptance of AVs, with positive affective attributes (happiness, satisfaction, and relief experienced when thinking about AVs) improving AV acceptance and negative affective attributes (worry, fear, and anxiety evoked when thinking about AVs) having the opposite effect.

2.1.2 Technology-Use Attributes

The importance of technology use variables for explaining AV acceptance for personal travel has been raised by many earlier studies. For example, Kyriakidis et al. (2015) note that the presence of automation technologies (such as automated cruise control) in an individual's current vehicle is correlated with their intention to use AVs in the future. Zmud and Sener (2017) observe that individuals who use smartphones, text messaging, Facebook and transportation apps are more likely to use AVs. The effects just discussed of technology-related variables on AV acceptance may occur through two rather distinct pathways. First, the use of a wide variety of technologies may be indicative of a generic tech-savvy lifestyle, marked by a high degree of reliance on computers and internet and communication technologies for daily activities. Individuals who lead a tech-savvy lifestyle would be more accepting of newer technologies in general. The second pathway is when an individual's actual experience with the use of specific technologies impacts AV acceptance. For example, if an individual has experienced some of the partial autonomous driving technologies such as cruise control or Tesla's autopilot, the experience may improve AV acceptance. While Lavieri et al. (2017) model the effect of technology use specifically in the former pathway sense using a latent construct for capturing the tech-savvy lifestyle, the other studies above do not make a distinction between the two different pathways that can lead to the effect of technology use on AV acceptance. Which pathway is at play (or the extent of influence of each pathway if both pathways play a role) becomes important for the design of policy actions, as we discuss later in this paper.

2.1.3 Perception of Safety and reliability

When it comes to the perceived safety of AVs, the context in which AVs are deployed and the design characteristics of AVs should also be considered. According to Kaur and Rampersad (2018), individuals are more willing to accept the use of AVs in closed environments such as university campuses. The use of AVs is also acceptable for finding car parks and cruising on highways as long as the driver can take back control when the vehicle leaves the highway. On the other hand, the use of AVs is less acceptable for use cases such as picking up and dropping off children and travel in areas with substantial pedestrian traffic. In the context of perceived safety for pedestrians, Miguel et al. (2019) observe that pedestrians feel safer using a crosswalk in front of an AV if the AV provides clear visual cues to acknowledge that it has identified human presence.

In a more recent and extensive survey of more than 30,000 individuals from more than 50 countries to understand the perceived safety of AVs, the awareness of AVs and the expectations of when the technology would be safe enough for use, Moody et al. (2019) find young, male and highly educated individuals to be more likely to perceive the use of AVs as being safe. They also note that individuals who are generally more aware of AVs perceived AVs to be safer. Waytz et al. (2014) and Lee et al. (2015) demonstrate that simple measures such as assigning the AV a name, a gender and a human-like voice also can improve an individual's trust and reliability in the technology. This has led to the suggestion of anthropomorphizing AVs. The Oxford English dictionary defines anthropomorphism as, "the attribution of human characteristics or behavior to a god, animal, or object."

2.2 Current Paper in Context

In this paper, we develop an analytic framework that models behavioral intent toward AVs at the individual-level. The specific behavioral intents considered (these are the main outcomes of interest) are (1) the level of overall awareness of the concept of AVs, (2) the individual's interest to use AVs, (3) the perceived safety of sharing the road with AVs, and (4) tendencies to favor or oppose regulations that restrict the use of AVs. Of these, the first outcome, while not explicitly a behavior intent variable, is considered in our framework because it is likely to be co-determined along with the remaining three behavior intent outcomes. In fact, as indicated by Piao et al. (2016), Ward et al. (2017) and Marikyan et al. (2019) in the socio-technical adoption literature, awareness and knowledge level of novel technologies play a critical role in affective responses, risk perceptions, and behavioral intentions to use the technologies. These studies also bemoan the lack of attention paid to awareness considerations, including in the widely used technology acceptance model (TAM) of Davis (1989) and Venkatesh and Davis (2000), which focuses on perceived usefulness and perceived ease of use but not antecedent awareness considerations. Also, the final outcome dimension in our framework (related to regulations) actually comprises three separate outcome variables associated with perceptions regarding three distinct regulations. The first regulation requires AVs to travel on dedicated lanes. In addition to the potential safety benefits, this regulation could also improve the efficiency of the transportation network, as demonstrated through simulations by Talebpour et al. (2017) and Yu et al. (2019). Countries such as China are taking the approach of building infrastructure that is easier to navigate for AVs rather than wait

for AVs to become safe enough to be used alongside human-driven vehicles (The Economist, 2019). The second regulation restricts AVs from traveling near certain areas such as schools and construction zones. Such a regulation would address the concerns of individuals regarding AV use in areas with high pedestrian traffic or for the purposes of picking up and dropping of school children (Kaur and Rampersad, 2018). The third regulation requires AVs to have a human in the driver's seat who could take control of the vehicle in an emergency situation. While several earlier studies have identified the specific environments and situations where AV use appears to be of general concern, our study addresses the important gap of investigating the extent of public support for AV use regulations at the individual level, and understanding how this support varies based on a multitude of individual-level factors.

The overall model specification in the current paper was influenced by the literature review summarized earlier. In particular, we consider the effects of socio-demographics, technology-use, and affective attributes on the behavioral intent toward AVs. Socio-demographic variables are considered exogenous to all aspects of the individual's behavior intent. However, drawing on the findings of Hohenberger et al. (2016), socio-demographic characteristics are assumed to have a two-fold impact: a direct impact as well as an impact mediated by affective attributes. The specific affective attributes considered in this study are enthusiasm and anxiety. In addition to the influence of socio-demographic and affective traits, we also include attributes related to technology use. Unlike earlier studies, we disentangle this technology use effect into a generic tech-savvy lifestyle pathway effect and an actual experiential pathway effect. If the former generic tech-savvy lifestyle pathway is dominant, then perhaps broad information campaigns and actions that target specific population groups to increase their level of technology awareness and use may help. On the other hand, if the actual experiential pathway effect is the dominant one, treatment measures that increase exposure to specific technologies would be the appropriate approach. To our knowledge, this is the first study that attempts to disentangle these two pathway effects, as well as to consider affective response effects in addition to both pathway effects of technology use.

In the context of the experiential pathway effect of technology use, the two specific technologies considered in the current paper correspond to voice-activated digital assistants (VADA) and industrial robots. These two technologies are specifically selected because they represent relatively recent technologies that serve to replace humans in certain tasks. Further, most of the popular VADA technologies (such as Apple's Siri, Amazon's Alexa, Microsoft's Cortana

and the Google Assistant) on the market today are highly anthropomorphized, and experience with these technologies can impact a person’s confidence in the ability of a machine to drive, which, until recently, was considered to be strictly confined within the human task domain.

Overall, the conceptual framework can be succinctly represented as shown in Figure 1. Socio-demographic variables impact the latent unobserved tech-savvy lifestyle variable as well as the individual-specific affective responses toward AVs. These latent constructs (shown in the figure in the ovals in the center panel) are likely to be a function of not only observed demographics, but also unobserved individual-specific characteristics, and so are considered to be stochastic in nature. Corresponding to these latent constructs are observed indicator variables (not shown in Figure 1) that help tease out the relationship between socio-demographics and the latent constructs. The socio-demographics, latent constructs and technology use/experience variables impact main outcome variables of interest. The framework enables the parsimonious analytic modeling of multiple endogenous outcomes, as discussed further in Section 4.

3 DATASET

3.1 The Survey

The dataset used in this study was collected as part of the American Trends Panel (ATP) survey conducted by the Pew Research Center (2019). The survey, initiated in 2014, used multiple instruments at different panel time points, each focusing on a specific topic deemed to be of national relevance. The sampling unit was an individual, with the panelists being recruited using a nationwide landline and cellphone random-dialing method. After the first recruitment drive in 2014, additional panelists were added using the same method in 2015 and 2017.¹ The survey was web-based and self-administered. Panelists that did not have access to the internet were provided with a tablet and wireless internet connection.

The current study mainly uses data on public sentiments toward a variety of automation technology applications that were collected between May 1 and May 15 of 2017 as part of the 27th wave of the ATP survey. Autonomous vehicles was one of several applications on which information was elicited from respondents (the other applications included digital assistants, robot caregivers for the elderly, software programs that can assist doctors, and computer programs for

¹ Recruitment drives were conducted after 2017 as well. For these recruitments, a random address-based sampling was done. However, in this study, we only use data from surveys that were administered in 2017.

making hiring decisions). In the survey, AVs were referred to as driverless vehicles or driverless cars and were succinctly defined 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, 2014).

The set of individuals from the 27th wave was targeted for another survey on wellbeing and political association in a 29th wave administered between September 14 and September 28 of that same year. It so happened that this 29th wave collected information on a few technology use variables (such as the ownership and use of computers, ebooks, and laptops) that were not collected in the 27th wave. These technology use variables from the 29th wave were appended to our primary data from the 27th wave for use in the current analysis.

3.2 Sample Description

The sample used in our analysis comprised 5341 respondents (all adults 18 years of age or over). The socio-demographic and other characteristics of the sample are discussed in the next few sections.

3.2.1 Individual Socio-Demographic Characteristics

Table 1 provides descriptive statistics of the socio-demographic variables from the sample. These descriptive statistics are compared against those of the entire U.S. population aged 18 or over as estimated by the U.S. Census Bureau (2019). The sample is reflective of the overall U.S. population with regard to gender and employment status. However, the sample shows an overrepresentation of individuals in the age group of 50 years or over (59.9% in the sample vs 44.7% in the population) and educated individuals (54.0% of the sample have a bachelor’s degree or beyond, while the estimated population share is 28.4%). The skewness toward older individuals is expected because younger individuals are less likely to respond to traditional survey recruitment methods such as random digit dialing (Cantrell et al., 2018). The higher sampling of educated individuals may be attributed to the technology-heavy content of the survey.

Overall, while the sample does differ from the U.S. adult population on the age and education distributions (implying that descriptive statistics for the endogenous variables of interest in this paper cannot be generalized to the U.S. adult population), it must be noted that the focus of the current paper is on estimating causal effects (how changes in exogenous demographics and

lifestyle/affective responses 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.

3.2.2 *Latent Construct Indicators*

The indicators of each latent construct (tech-savviness, enthusiasm, and anxiety) used in the modeling are presented in Table 2a, together with their sample distributions. The latent construct of tech-savviness has been widely used in the previous literature when exploring the use and acceptance of new urban mobility services (see, for example, Astroza et al., 2017; Lavieri and Bhat, 2019; Velázquez Romera, 2019). The indicators for this construct in the current paper capture the use of what has now become relatively ubiquitous technology, including the frequency of use of computer and internet usage, as well as the use of a laptop, tablet/e-book reader, and voice activated digital assistants (VADAs) in smart devices. The descriptive statistics in Table 2a for these indicators show, not surprisingly, that a vast majority of respondents (87.2%) use computers most days or every day, and a similar vast majority (88.2%) access the internet at least once each day. A smaller percentage (73.5%) use laptops in their daily lives, and an even smaller percentage (51.2%) use tablets or e-book readers. The last indicator pertains to VADA use. This question was asked of only about half of the respondents, with the other half being asked questions regarding the use of other automation technologies that are not relevant to this study (such as drones and computer programs that filter and score job applications). The black shading in Table 2a in the third column for the row corresponding to VADA use indicates this situation, with 51% of respondents not presented with the VADA use question. As Table 2a shows, among those who were asked the VADA use question (see numbers in parenthesis in this row), around half of the respondents (51.8% to be precise) indicated that they actually do use VADA. This rather

substantial use of VADAs is a little surprising, given that VADAs have been relative newcomers in the technology market, but may be attributable to the fact that our sample is highly educated.

The latent constructs associated with affective responses (enthusiasm and anxiety) were elicited in the context of AV development and not specifically in the context of using AVs or sharing the road with AVs. In particular, the indicators were in the form of questions that sought how enthusiastic and how worried (a metric of anxiety) the respondent felt about AV development, obtained on a four-point ordinal Likert scale. However, even if the indicators refer to affective responses to AV development, they allow us to construct stochastic affective response latent constructs for use to explain the main outcomes related to AV awareness, AV interest, and AV safety and regulations. The last two rows of Table 2a provide the descriptive statistics on the affective response indicators. More than half of the respondents (57.7%) are “not at all enthusiastic” or “not too enthusiastic” about AV development, while just about half of the respondents (51.3%) indicate that they are “somewhat worried” or “very worried” about AV development. These statistics are interesting, and perhaps suggest that, even as our sample is highly educated, the higher loading toward older individuals may be leading up to more skepticism regarding AV development (especially because older individuals are the ones who have been used to driving longer and are likely to be less willing to give up that control to a machine relative to younger individuals). Our empirical results (discussed later) indeed support this notion. Indeed, even from a descriptive standpoint, we noted that, while only 42.6% (50.1%) of those in the 18-29 year age group reported being “not at all enthusiastic” or “not too enthusiastic” (“somewhat worried” or “very worried”), the corresponding numbers rose to 63.5% (53.3%) in the 50+ age group.

3.2.3 Technology Use

As discussed earlier, multiple earlier studies have investigated the actual effects of technology use on intention to purchase/use AVs, though there has been little to no investigation on how technology use/ experience may affect the perceived safety of sharing roads with AVs and AV regulation support (the main focus of the current study). Three variables are used to represent technology use/experience effects (in the rest of this paper, we will use the generic term “technology use” to refer to “technology use/experience”): use of VADAs (which also serves as an indicator to capture a tech-savviness lifestyle; see previous section), experience with the use of

VADAs, and the extent/nature of the impact of industrial robots on work-related activities. Information regarding experience using VADAs and the extent of impact industrial robots at work were elicited on an ordinal scale. Table 2b presents the descriptive statistics on these technology use variables. For completeness, we reproduce the binary shares for VADA use. The second variable corresponding to experience with VADA use was sought from only those who were asked the VADA use question and who indicated that they actually use VADAs (that is, this question was only asked of 25.4% of the entire sample; please see the 74.6% (=51.0+23.6) figure in the last column for this row, which is blacked out to indicate the share of individuals who were not presented with this “experience with VADA use” question). Among those who were presented with the question, a majority (86%) indicate that VADAs respond accurately some or most of the time, while 14% indicate that they do not respond accurately very often (see the numbers in parenthesis in the first three columns in the row). Finally, the question pertaining to the extent/nature of impact of industrial robots on work activities was asked of the 61.2% of employed individuals (and not of the 38.8% of unemployed individuals). The distribution in Table 2b for this variable is not surprising, and indicates that a majority of workers (60.2%) report no impact of industrial robots on work activities (suggesting non-use of industrial robots at the work place). Among those workers who report some impact, a majority see the impact as being positive.

Two important notes are in order here. First, it is possible that experience with VADA use itself may be another indicator for tech-savviness (and not just VADA use alone; that is, a tech-savvy person may not only be more likely to use VADAs, but may also be more likely to report a positive experience with VADAs). However, in our empirical analyses, after employing VADA use as an indicator of tech-savviness, VADA experience did not provide any additional value in pinning down the tech-savviness latent construct, and so was removed as an indicator. This result suggests that while tech-savviness drives the consideration (or not) of VADA use, experience with the VADA itself is entirely independent of tech-savviness levels and is simply an outcome of the perceived convenience and effectiveness of the VADA. Of course, this result is consistent with the larger customer service and information science literature indicating that, while new products and services can be targeted toward specific tech-savvy groups to increase initial uptake, the quality and effectiveness of the product (that drives experience) is also important in maintaining long-term customer base (see, for example, Pan et al., 2011; and Peng et al., 2017). The result here also adds further credibility to our framework that dis-entangles the technology use effect into a generic

tech-savvy lifestyle pathway effect and an actual experiential pathway effect. Second, we consider the extent/nature of the impact of industrial robots at work to be an exogenous variable unaffected by tech-savviness or socio-demographics, because this is (at least at this time) a very specialized technology. The extent/nature of exposure to industrial robots at the work place is more likely to be driven by market pressures and competitive forces, rather than being within the immediate control of the individual. Besides, from an estimation standpoint, leaving the industrial robot variable as a completely exogenous variable lends additional stability in disentangling the two different pathway effects of technology use.

3.2.4 *Main Outcome Variables*

Table 3 presents descriptive statistics for the six main behavioral intent outcome variables related to AV awareness, AV interest, perceived safety of sharing the road with AVs, and AV regulations. The first row of Table 3 shows the response to the AV awareness question: “How much have you seen or heard about the effort to develop driverless vehicles – that is, cars and trucks that can operate on their own without a human driver?” Individuals could respond on a three-level ordinal scale: “Nothing at all”, “A little” or “A lot.” A large proportion of the sample (96.6%) had heard at least “a little” about AVs. For comparison, Moody et al. (2019) asked a similar question in a 2017 survey of 33,958 survey participants spread across 51 countries. The share of respondents who had heard at least “a little” about AVs in that survey was only 75.2%. However, Moody et al. (2019) note that individuals from the U.S. are much more likely to be aware of AV technology than individuals in other countries. The interest for riding in an AV (henceforth referred to as AV interest) was elicited with the following query: “Would you, personally, want to ride in a driverless vehicle if you had the opportunity?” Slightly more than half of the respondents would not make use of such an opportunity. This is in line with many of the previous studies that found a near-even split of individuals regarding their preference for AV use (Capgemini Research Institute, 2019; Zmud and Sener, 2017). The third outcome variable associated with the perceived safety of sharing the road with AVs (PSSRAV) was elicited using the following question: “How safe would you feel sharing the road with a driverless passenger vehicle?” Most individuals (about 73%) consider sharing the road with an autonomous passenger vehicle to be “Not too safe” or “Somewhat safe”, with about an equal share of individuals in the extreme categories of “not safe at all” and “very safe”. Finally, the three AV regulations for which preferences were elicited (on a four-point Likert

scale from “strongly oppose” to “strongly favor”) were as follows: (1) “Requiring [AVs] to travel in dedicated lanes,” (2) “Restricting [AVs] from traveling near certain areas, such as schools,” and (3) “Requiring [AVs] to have a person in the driver’s seat who could take control in an emergency situation.” A clear majority of the individuals favor all the three regulations. This strong support for AV regulation in general suggests lingering concerns over handing over full control to the vehicle. The most favored regulation is the one requiring vehicles to have back-up drivers. Indeed, in an earlier study conducted by Schoettle and Sivak (2014), 46.1% of the individuals who said they would use AVs stated that they would be watching the road even if they are not driving. The least favored regulation (which still is favored by 65.7% of respondents) is the one that restricts AVs from traveling near areas such as schools.

4 METHODOLOGY

The modelling methodology adopted is based on the Generalized Heterogeneous Data Model (GHDM) developed by Bhat (2015), a methodology previously employed to analyze AV adoption and use by Lavieri et al. (2017), but not issues related to AV awareness, acceptance, safety perceptions, and regulations. The GHDM represents a comprehensive approach that allows jointly analyzing multiple outcome variables of interest, while controlling for observed and unobserved factors that may affect individuals’ behavioral intents. The framework, in its original form, supports the modeling of a mixture of different types of endogenous outcome variables, including continuous, nominal, ordinal, count, and multiple discrete-continuous variables. In our study, the framework simplifies because all the outcomes are ordinal (some of the outcomes are binary, but such outcomes are but a special case of ordinal outcomes). The mathematical formulation of the simplified GHDM framework with only ordinal outcomes is presented in an online supplement to this paper (see <https://www.cae.utexas.edu/prof/bhat/ABSTRACTS/TechAV/OnlineSupp.pdf>); here we only present a more intuitive discussion of the model.

There are two components to the GHDM model: (1) the latent variable structural equation model (SEM), and (2) the latent variable measurement equation model (MEM). As illustrated in Figure 2, the SEM component defines each latent construct (represented as ovals in the middle panel of the figure) as a function of exogenous socio-demographic variables (left side of the figure) and an unobserved error term (not shown in the figure). Each error term represents the effect of unobserved individual factors on a specific latent construct. Let these unobserved factors be

denoted by η_1 , η_2 , and η_3 (corresponding to one of the three latent constructs in Figure 2) and collect them in a vector $\boldsymbol{\eta}$. We assume $\boldsymbol{\eta}$ to be multivariate standard normal with a mean vector of $\mathbf{0}$ and a correlation matrix of $\boldsymbol{\Gamma}$ with three possible correlation elements (due to identification considerations, the variances of the individual $\boldsymbol{\eta}$ elements need to be normalized to 1; see Bhat, 2015). The latent constructs are stochastic because of the presence of the random elements, and, by definition, are not observed. The SEM model relationship between the socio-demographic variables and the latent constructs, as well as the correlation matrix elements of $\boldsymbol{\Gamma}$, are not directly estimable, but are estimated through observations on the latent construct indicators (not shown in Figure 2) and the endogenous outcomes of interest (shown toward the right side of Figure 2). The exogenous socio-demographic variables, the latent constructs, and the technology use variables all then serve as determinants of the underlying latent propensities of the observed ordinal/binomial outcomes characterizing the endogenous variables of interest and the indicator variables. This is represented by the MEM relationship in Figure 2.

The latent constructs of tech-savviness and affective responses in Figure 2, in addition to capturing important lifestyle preference and emotive effects toward AV behavioral intent (the outcome variables of interest), also serve as vehicles to allow the parsimonious joint modeling of multiple outcomes of interest in the MEM component. Specifically, the error terms of the latent variables permeate into the MEM part and establish a parsimonious dependence structure among all endogenous variables. For example, as found in our empirical results, the tech-savviness and anxiety latent constructs positively impact AV awareness and negatively impact perceived safety sharing the road with AVs (PSSRAV). Tech-savvy individuals may have a lower PSSRAV because such individuals are more acutely aware of the technical challenges involved in the safe deployment of AVs, while, as Yang and Kahlor (2013) suggest, negative affective reactions of anxiety lead to more active information seeking as such feelings evoke a sense of information insufficiency. These latent construct effects imply a negative error covariance between the AV awareness and PSSRAV endogenous outcomes (through the error term η_1 embedded in the tech-savviness latent construct and the error term η_3 embedded in the anxiety latent construct). Ignoring this negative covariance (that is, ignoring the effects of tech-savviness and anxiety latent constructs), therefore, will lead to a dampening of any positive impact of improving AV awareness on PSSRAV (and, therefore, would incorrectly underplay actions that may be oriented toward enhancing AV awareness as a policy instrument tool to improve PSSRAV). Another example of

this situation is in the effect of PSSRAV on support for AV regulations. Tech-savviness, for example, negatively impacts both PSSRAV and support for AV regulations in our results (that is, generically tech-savvy individuals are more concerned about safety when riding alongside AVs, but also do not favor AV regulations). Ignoring the resulting positive covariance between PSSRAV and support for AV regulations would lead, incorrectly, to the conclusion that policy actions targeted toward improving PSSRAV would not be as effective in reducing opposition to AV regulations as it really would be.

Overall, an advantage of using a framework with mediating stochastic latent constructs is that, in addition to capturing lifestyle/emotive effects and enabling better data fit, it allows us to parsimoniously parameterize the covariance matrix of the endogenous variables (the endogenous variables include the indicators of the latent constructs and the six main outcome variables of interest (listed in the right panel of Figure 2). The GHDM controls for error correlation due to the joint modeling of these variables, and accommodates recursive effects among them.² Multiple recursive directionalities between endogenous variables were tested in this research. The best data fit was obtained in the causal specification considering AV awareness influencing PSSRAV, and PSSRAV and the interest in riding AVs impacting the three AV regulation variables. This is the specification discussed in more detail in the next section. However, to be kept in mind is that the model is still a joint model that considers all the endogenous outcomes as a single bundled choice process, because of the error correlations generated across the endogenous outcomes through the stochastic latent constructs.

5 EMPIRICAL RESULTS

This section summarizes the main results from the analysis conducted in this research. In the estimations, some individuals were not asked questions related to the use of VADAs. So, whenever the use of VADAs is considered, we also include a separate dummy variable category identifying whether the individual was presented with the VADA use question or not. This has the result of using individuals with reported VADA use to assess appropriate behavioral intent effects, while also using all individuals when estimating the effects of other model variables. Of course, we

² In joint limited-dependent variables systems in which one or more dependent variables are not observed on a continuous scale, such as the joint system considered in this paper that has ordinal, binomial, and nominal discrete dependent variables, the structural effects of one limited-dependent variable on another can only be in a single direction. See Maddala (1986) and Bhat (2015) for a more detailed explanation.

would hope that the coefficients on such dummy variables would not be statistically different from zero, which would signify that the selection of respondents for presentation of the VADA use question was random.

A whole suite of different specifications was attempted and the final specification was obtained based on a systematic process of testing alternative combinations of explanatory variables and eliminating statistically insignificant ones while also moving toward parsimonious specifications. Initially, the correlations between the latent constructs were fixed to zero and a wide range of specifications with different endogenous relationships (i.e., relationships between the latent constructs and the endogenous variables and between endogenous variables themselves) were tested. For these specifications, all the relevant exogenous variables were included in the specifications for the latent constructs and endogenous variables. From this set of specifications, the set of endogenous relationships with the best convergent likelihood fit was identified. This set of endogenous relationships formed the basis for the specification used in the final analysis. Subsequently, the exogenous variables that were insignificant (at the 90% level) were sequentially removed one at a time. In this process of removing exogenous variables, if an endogenous relationship became insignificant, this was also removed. Finally, once all the significant endogenous and exogenous effects were identified, the model was re-estimated allowing for correlations between the error terms of the latent constructs.

5.1 Estimation Results and Inference

Although all model parameters were estimated jointly, they are presented in this section in parts to facilitate an organized discussion of the results.

5.1.1 Tech-Savviness and Affective Response Latent Constructs

The structural relationships between socio-demographic variables representing lifecycle stages and the latent constructs are presented in Table 4. The results suggest higher tech-savviness among younger individuals, possibly because such 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, recent research (see Berkowsky et al., 2017; Rogers et al., 2017) indicates that it takes a greater effort for older generations to use digital devices as proficiently as younger individuals, because

of which older generations have a lower perception of ease of use, as well as actual usefulness, of many internet features, apps, and technologies. Another interesting explanation is that avoiding assisting technologies is an important vehicle for older individuals to maintain a self-perception of being in control, thus raising their mental self-esteem at a stage of life when their physical self-esteem may not be as high as during their yester years (Marikyan et al., 2019 also allude to this point in their analysis of smart home technology adoption). All of these considerations combine to explain the higher tech-savviness among the younger “digital native” generation than their older peers. On the other hand, there does not seem to be any difference in tech-savviness between men and women, a finding also observed by Laverie and Bhat (2019). Tech-savviness is higher among individuals with high educational attainment and who are employed. This is not surprising, because a thorough grasp of ICT use is essential to succeed in today’s increasingly knowledge networking-based economy (van Laar et al., 2017). Finally, in the context of tech-savviness, a lower household income (relative to a higher household income) is associated with lower tech-savviness. Wealthier individuals have the financial “firepower” to afford a larger number of technological devices and are usually the first to have access to new technologies that are typically expensive when first released (see, for example, Laverie et al., 2017; Liu and Yu, 2017).

As for the affective latent constructs (the second and third columns in Table 4), unsurprisingly, the socio-demographic variable effects are consistently opposite of one another on the positive affective attribute of enthusiasm and the negative affective attribute of anxiety. Younger individuals are more enthusiastic and less anxious about AVs than their older counterparts. The advent of AVs could engender a disruptive change in the way of life for older individuals, especially because older individuals are generally more satisfied with their circumstances, “having adjusted their aspiration levels downwards to meet the reality of actual life situations” (Whitbourne, 1986). Further, older individuals are typically less open to change and new experiences (Kessler, 2009, and Gonzalez-Gutierrez et al. (2005). In particular, as adults progress into middle and later adulthood, they become less and less interested in, for example, gathering new information or meeting new people. On the other hand, as Hoyer and Ridgway (1984) and Milojev and Sibley (2017) have noted, childhood and young adulthood are characterized by a higher level of curiosity and stimulation, and a need to seek more variety in their daily lives. The results also indicate that women are less likely than men to be enthusiastic, and more likely than men to be anxious, about AVs, the latter finding also documented by

Kyriakidis et al. (2015), Hohenberger et al. (2016) and Ward et al. (2017). Women tend to be more risk-averse than men (Borghans et al., 2009) and the prospect of opening the community to an untested new technology may appear daunting to them. 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). Finally, the less-educated and lower income segments tend to be less enthusiastic and more anxious about AVs relative to more educated and higher income segments, respectively. The worry of these demographic groups may be driven by their concern about the potential fall in low-skilled employment opportunities if AVs become prevalent (Beede et al., 2017; Liang, 2017).

The estimated correlations between the error terms of the latent constructs (see bottom of Table 4) are as one would expect. Unobserved factors that increase an individual's tech-savviness also tend to make the individual more enthusiastic and less anxious about AVs, while unobserved factors that make an individual more enthusiastic about AVs also tend to make the individual less anxious about AVs.

The SEM estimation results above are made possible through the observations on the endogenous variables, which include the latent construct indicators and the six endogenous outcomes of interest (see Figure 2). To conserve on space, and because the loadings of the latent constructs on the construct indicators are not of primary interest in this paper, we relegate these loading results to the online supplement. Suffice it to say that the loadings were significant and had the expected sign.

5.1.2 AV Awareness, AV Interest (to Use) and PSSRAV

Table 5 presents the coefficients estimated for the AV awareness, AV interest, and perceived safety of sharing the road with AVs (PSSRAV). These coefficients refer to the impact on the underlying latent propensity characterizing these ordinal outcomes, which are then mapped to the actual observed outcomes through the constants and the threshold values (presented at the bottom of Table 5; the constants and thresholds do not have any substantive interpretations).

Latent construct effects: The direction of impacts of the latent constructs are all reasonable. In addition to those discussed in presenting the modeling framework in Section 4, the latent construct

effects indicate the positive impact of enthusiasm and the negative impact of anxiety on the interest to ride in an AV.

Effects of socio-demographic attributes: The sociodemographic effects in Table 5 provide the direct effects of socio-demographics, beyond their indirect effects mediated through the latent constructs of tech-savviness and the affective responses (the indirect effect of a socio-demographic variable is the product of the coefficient of the latent construct in Table 5 and the coefficient of the socio-demographic attribute for the latent construct in Table 4).

The model results in Table 5 indicate that individuals aged less than 50 years of age are less aware of AV developments than their younger peers. That is, an older individual at the same level of tech-savviness and affective response levels (and at the same levels of other socio-demographic variables) as a younger individual is likely to be more aware of AVs. Indeed, while only 38% of the individuals aged less than 50 in our sample dataset remarked as having heard “A lot” about AVs, this share rose to 44% among individuals aged 50 or above. This result is surprising considering that older individuals have been found to be less aware of AVs in some earlier studies (Kyriakidis et al., 2015; Moody et al., 2019; Schoettle and Sivak, 2014). However, in a study of public awareness of smart city services in the City of London, Peng et al. (2017), like in our study, find that the younger generation is less aware of smart transportation technology related to parking. There may be three reasons for such a finding. First, those below the age of 50 years are likely to be more time poor because of juggling career pressures and family pressures. As observed by Harvey and Mukhopadhyay (2007) and Williams et al. (2016), the convergence of career pressures and life-cycle pressures for working parents with children is a leading cause for time poverty. We suggest that such time poverty can logically lead to what we label as “knowledge poverty”, in the sense that time-poor individuals are not able to engage much with knowledge networks to keep up with, and gain awareness of, futuristic technology (in our survey, unfortunately, we did not have information on the presence of children or household structure, and so age is likely to be a stand-in proxy for life-cycle). Related to this issue is that popularity and acceptance in social circles are critical issues to construct “self-identity” for younger digital natives, leading them to be focused on the “now” and “here” and not give attention to the “tomorrow”, even when they have some time (López et al., 2017, and Mathuews, 2018). Second, the younger generation of digital natives require more visually-rich, colorful, and fashionable

knowledge dissemination styles to catch and keep their interest, according to studies in the knowledge networks and advertising literature (see, for example, Smith, 2008, and Scheffels and Lund, 2013). Typical media news stories, textually-heavy information, and scholarly/pedantic pieces, which is where much of the AV information resides, tend to be spurned by the younger generation. A third explanation is that traditional TV and radio media, which constitute important sources of information on automated driving for older individuals, tend to focus more on risks (such as accidents) than benefits (see Ward et al., 2017). This immediately gets on the radar of older individuals. However, notwithstanding the reasons provided above for our finding of lower AV awareness among younger adults relative to their older peers, we must note that the estimated direct effect of age is considerably dampened by the indirect effect through the latent constructs, although there is still a net lower AV awareness among younger individuals (for example, the direct effect of those in the 18-29 year age group from Table 5 is -0.525, while the indirect effect turns out to be +0.379, leading to a net effect of -0.146 for this sociodemographic group). Also of note is that, after accommodating for the indirect effects through latent constructs and the AV awareness variable itself, age did not have any statistically significant direct impact on AV ridership interest or perceived safety (PSSRAV). That is, any age effects on AV ridership interest and safety perceptions are transmitted primarily through the tech-savviness, affective emotions, and AV awareness considerations. The advantage of using our path analysis is that it provides this kind of information regarding the causes for age-related variations, so that appropriate policy instruments may be designed (as discussed further in Section 6).

The gender effect indicates that women constitute another demographic group that is less aware of AVs. This is in concordance with past literature that suggests a lower level of awareness and interest in AVs among women (Schoettle and Sivak, 2014; Zmud and Sener, 2017), though this difference may also be attributable to women (especially working women) being more time-poor than men. This direct gender effect is further reinforced marginally through the indirect effects, though the indirect effects through the “enthusiasm” and “anxiety” latent constructs effectively cancel out each other (the direct effect of gender is -0.535, while the indirect effect is -0.043). This result suggests that efforts to improve AV awareness need to be targeted at presenting women with more opportunities to absorb information about AV developments, rather than, for example, through tech-savviness campaigns. Less-educated individuals are also less aware of AVs, possibly because such individuals have less access to knowledge network groups that discuss the

progress of advanced technologies such as AVs. The direct effect for the “high school or less group” is -0.174, while the indirect effect through the latent constructs is -0.315; the direct effect for the “some college or associate’s degree” is 0.000, while the indirect effect is -0.171. Again, the suggestion is that the way to improve AV awareness among the less educated is through direct campaigns that present more opportunities for consumption and absorption of AV information. Further, less educated individuals are also more concerned about PSSARV, perhaps because of concerns and the uncertainties of how AV technology may reshape their livelihoods.

Interestingly, the results indicate that, in terms of a direct effect, employed individuals are less aware of AVs. This may simply be a reflection of time availability, especially given that our sample, even if it contains unemployed individuals, is also rather highly educated. Thus, those who are not employed are relatively well educated and also have time, which can combine to provide this result. Employed individuals are, however, likely to be more comfortable driving alongside AVs on the roadway, perhaps because they are routinely subjected to long commute delays and are more likely to encounter traffic accidents during their travel, leading to a perception that “machines are likely to be better than the human driving next to me.”

Finally, in the category of socio-demographics, low-income individuals are less likely to have heard of AVs, presumably because of the limited social capital at their disposal and the restricted reach of their knowledge networks, which in turn can modulate and/or meter incoming information flow (Qureshi et al., 2018). The direct effect in Table 5 corresponding to low income individuals is further reinforced about exactly equally (in magnitude) by the indirect effects. Interestingly, though, the results also indicate that, based on the direct effect, low-income individuals are more interested in using AVs. This may be tied to the framing of the AV interest question in the ATP survey, which was not whether they would be interested in purchasing and riding in an AV, but in the context of whether they would be interested in riding in an AV if an AV were made available to them. For low-income individuals, this would clearly represent a novelty that would otherwise be outside their financial reach, which may have led to more of an interest from this sociodemographic group relative to their higher income peers (who may have viewed the same question in the context of AV safety). The fact that no other sociodemographic variable loads on the AV interest variable, as well as that AV interest does not influence PSSRAV, lends further credibility to our speculation. Besides, if we consider both the direct and indirect impacts through the latent constructs, individuals from low-income households are distinctly less

inclined to ride AVs (the direct effect from Table 5 is 0.212, while the indirect effect is -0.650, with the net effect being -0.438). The clear suggestion is that low income households are reluctant to ride in AVs mainly because they are less enthusiastic and more anxious about the technology. These individuals may become more interested in using AVs once their concerns that cause anxiety are addressed. This overall effect is consistent with that reported in earlier studies (Capgemini Research Institute, 2019; Kyriakidis et al., 2015).

Effects of technology use: Even after controlling for the effect of a tech-savvy lifestyle, the effects of exposure to certain specific technologies on AV interest and PSSRAV are significant. As we hoped, the dummy variable for identifying individuals for whom the VADA use question was not asked turned out to be statistically insignificant in its effect on all three outcome variables in Table 5. Beyond this, VADA use is positively associated with AV interest, while a positive experience with VADA bolsters PSSRAV. As mentioned earlier, most of the popular digital assistants are highly anthropomorphized. Therefore, a digital assistant demonstrating its ability to accurately comprehend and respond to human speech should boost consumer confidence in the ability of machines to safely perform tasks such as driving. Indeed, several studies in the area of human-robot interactions have suggested anthropomorphizing machines as a strategy for increasing confidence in the competence and trustworthiness of machines (Lee et al., 2015; Waytz et al., 2014). Another reason for the positive effect of VADA performance on positive safety perceptions is that both the technologies have been made possible only because of advances in machine learning and big data processing techniques, and a good experience with one therefore should also lead to more favorable assessments of the other. This kind of cross-over confidence among related products is well established in the consumer choice and information science literature (see, for example, Ching et al., 2017).

A positive experience with industrial robots did not provide a similar increase in interest in AVs or PSSRAV, possibly because most of these robots are not anthropomorphic and are designed to perform a specific repetitive set of tasks that cannot readily be equated with driving. On the other hand, a negative experience with industrial robots tends to lower PSSRAV. The nature of the negative experience with robots was not specifically elicited in the survey, but social-psychological studies (see, for example, Mittal et al., 1998; Tversky and Kahneman, 1991) clearly indicate asymmetry when evaluating important life decisions (such as giving up control to a

machine) wherein risks and negative experiences get exaggerated and benefits and positive experiences get underplayed.

Recursive effects: Gaining more awareness of the development of AVs raises confidence in sharing the road with AVs, consistent with earlier studies in the socio-technical adoption literature. This empirical finding lends further support for our decision to model AV awareness along with other AV behavioral intent outcome variables. In general, higher awareness of an emerging technology provides a greater sense of transparency, which leads to higher confidence in the technology (De Fine Licht, 2014).

5.1.3 Support for Regulations

The estimated coefficients associated with the preferences for regulations are presented in Table 6. Once again, these coefficients denote only the direct effects.

Among the latent constructs, tech-savviness is associated with a reduced support for regulations (after controlling for the perceived safety of sharing the road with AVs), even after controlling for its effect through the PSSRAV effect. This is quite reasonable, given tech-savvy individuals, even though they appear to have heightened safety concerns in allowing AVs to travel alongside human-driven vehicles, would rather not see innovation in technology be stifled by premature regulations. Interestingly, the effects of affective attributes on regulations get solely manifested through AV interest and PSSRAV, which is not surprising given that PSSRAV is likely to be paramount in support (or no support) for regulation.

Among the socio-demographic variables, younger individuals, relative to their older peers, particularly oppose the mandate of requiring dedicated AV lanes. Another way to see this is that older individuals are much more supportive of the regulation for dedicated AV lanes. This result may be explained through the theory of innovation resistance in the information science literature (see Mani and Chouk, 2017; Ram and Sheth, 1989). Specifically, older individuals might see AVs as disrupting the existing driving environment and requiring a departure from well-established habits/norms of driving during their regular travel, and therefore resist allowing AVs to drive alongside their human driven vehicles. Women and employed individuals, relative to men and unemployed individuals, respectively, consistently support all three regulations. This suggests that, even after accommodating for affective response effects, tech-savviness effects, and AV

awareness/interest/PSSRAV effects, there are still remnant gender/employment effects in support for regulation, an issue that certainly warrants additional study to further “peel the onion”. Finally, among the recursive effects, as expected, AV interest leads to less support for regulations as does a higher PSSRAV.

5.2 Goodness-of-Fit Statistics

In this section we compare the goodness of fit of the GHDM model against an independent ordered probit (IOP) model that ignores the endogeneity among the different outcome variables caused through the latent stochastic constructs of tech-savviness and affective responses. The GHDM model and the IOP model are not nested, as the latter model does not provide a mechanism to incorporate the latent constructs. Therefore, for a fair comparison between the GHDM and IOP models, we compute the average probability of correct prediction and the likelihoods for only the main outcome variables of AV awareness, AV interest, perceived safety of sharing the road with AVs (PSSRAV) and support for the three AV regulations. Also, to recognize the effects of socio-demographic and technology use variables to the fullest extent possible in the IOP model, the full set of these variables are included as explanatory variables. Table 7 provides multiple disaggregate measures of fit for the GHDM model and the resulting IOP model.

The GHDM model outperforms the IOP model with respect to the average probability of correct prediction of the joint combination of the main outcomes. These average probabilities may appear low, but considering that the six outcome variables can produce a total of $3 \times 2 \times 4 \times 4 \times 4 \times 4 = 1536$ outcome combinations, the value of 0.0119 for the GHDM model is more than 18 times the probability of correct prediction due to random chance (0.00065). The predictive log-likelihood at convergence of the GHDM is also quite a bit higher than for the IOP, though the models cannot be compared using a nested likelihood ratio test. But we can use the familiar non-nested likelihood ratio test to informally compare the two models, because the indicator variables used in the measurement equation of the GHDM are included solely for the purpose of model identification and do not serve any purpose in predicting the endogenous choice bundle of interest once the model is estimated. To do so, we evaluate a predictive log-likelihood value $L(\hat{\theta})$ for each of the two models at the model convergent values, focusing only on the primary outcome variables of interest. Then, one can compute an informal predictive adjusted likelihood ratio index (PALRI) of each model with respect to the log-likelihood with only the constants as follows:

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

where $L(\hat{\theta})$ and $L(c)$ are the predictive log-likelihood functions at convergence and at constants, respectively, and M is the number of parameters (not including the constant(s) for each dimension and not including the ordinal indicators) estimated in the model. 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 $\Phi\{-[-2\tau L(c) + (M_2 - M_1)]^{0.5}\}$ in the asymptotic limit (however, this is only an informal test, because, in the estimation of the GHDM, the indicator variables are also included). A small value for the probability of chance occurrence suggests that the difference is statistically significant and that the model with the higher value for the adjusted likelihood ratio index is to be preferred. The PALRI values are provided in the last row of Table 7. The non-nested adjusted likelihood ratio test (in its informal version used here) returns a value of $\Phi(-42.9)$, which is literally zero, reinforcing the superior $L(\hat{\theta})$ from the GHDM model compared to the IOP model.

6 IMPLICATIONS

The estimation results in the previous section provide insights into direct and overall indirect effects. However, for policy analysis purposes, it would be helpful to break down the impact of each socio-demographic and technology use variable on the AV interest (to ride) and the PSSARV outcome variables, based on the contribution of the variable to each of five sub-effects: tech-savviness enhancement effect, enthusiasm promotion effect, anxiety-reduction effect, AV awareness increase effect, and the remaining direct effect. This partitioning can be done using the Average Treatment Effect (or ATE effect; see Angrist and Imbens, 1991, and Heckman and Vytlacil, 2000), which is a metric that computes the impact on a downstream posterior variable of interest due to a treatment that changes the state of an antecedent variable from A to B . For example, if the intent is to estimate the treatment effect of improving the experience with VADAs on PSSRAV, A can be the state where the individual had no experience with VADAs, and B can be the state where the individual has had a good experience with VADAs. 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 . The procedure for making predictions with the estimated model and

computing the ATEs is detailed in the online supplement. If a variable impacts AV interest and/or PSSRAV through a mediating latent variable (such as sociodemographic effects through the tech-savviness construct), one can use the estimates from Tables 4 and 5 to partition out the ATE by its sub-effects. When the mediating variable is ordinal (such as AV awareness), the sub-effect will be the product of the coefficient of the mediating variable in Table 5 with the ATE on the mediating variable.

For presentation ease, in this paper, we only report the ATEs for a change from the lowest extreme to the highest extreme for the antecedent variable (for example, we focus only on the change from the base age category of 50+ to the youngest category of 18-29 years and only consider the change from the base category of high education (bachelor's and above) to high school or less. For the case of experience with VADA, we consider the base case of not having used VADA and the post-treatment case of having used VADAs and finding VADAs to respond accurately most of the time. Also, we confine our attention to the ATE effect for the "yes" category for AV interest. For the PSSRAV variable, we combine the "safe" and "very safe" categories into a single category for the ATE effects computation. To compute the relative magnitudes of the contribution of each 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 Table 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).

Once the sub-effects of the socio-demographic and technology-use on AV ridership and PSSRAV are determined, we proceed to determine the ATE effects for (a) tech-savviness, (b) the socio-demographic variables of age, female gender, and employment, (c) AV ridership, and (d) PSSRAV on the AV regulations. For the tech-savviness effect, we assume a pre-treatment scenario of all individuals having a tech-savviness equal to the 25th percentile value of tech-savviness in the sample. The post-treatment tech-savviness is set to the 75th percentile value. The ATE of increasing PSSRAV is obtained by setting the base scenario as a combined single "not safe at all"/"not too safe" category and changing this in the policy scenario to another combined "somewhat safe"/"very safe" category.

The ATE effects in Table 8 and Table 9 enable us to extract important insights for policy actions that can lead to AV interest promotion, safety perception enhancement, and lower support

for AV regulation. The ATE values (in the last column of the tables) are to be interpreted as follows. Consider the first ATE effect of age on the “interest in riding AVs”. The last column of the first numeric row corresponding to this variable shows a value of 0.229. This implies that if 100 older individuals were replaced by 100 younger individuals, 23 additional individuals (of the 100) would become interested in riding in an AV. Other ATE values may similarly be interpreted. The “% contribution by mediation through...” columns are to be interpreted as follows. The value of 92.6 in the column for “enthusiasm increase” for the age variable (change from the 50+ age category to the 18-29 years age category) indicates that, in terms of magnitude, 92.6% of the sum of the contributions of each sub-effect (ignoring directionality) to the ATE increase in AV interest is due to an enthusiasm increase sub-effect. The value of 7.4 in the column for “anxiety reduction” in the same row indicates similarly that 7.4% of the sum of the contributions of each sub-effect (ignoring directionality) is due to an anxiety reduction sub-effect. Both of these effects have a positive sign, indicating that the age treatment leads to both an enthusiasm increase sub-effect and an anxiety reduction sub-effect (that reinforce each other). On the second row, however, there are negative signs on the percentages for the treatment corresponding to gender, which indicates that women are less enthusiastic and have a lower level of anxiety reduction (implying higher anxiety) than men, which again reinforce each other. In some cases, there is a combination of positive and negative sub-effects, as in the case of the age effect on PSSRAV. Here, a change from the “50+ years” to the “18-29” age category leads to an ATE effect decrease on PSSRAV through a tech-savviness increase sub-effect (that is, the age change leads to an increase in tech-savviness, which then reduces PSSRAV, as discussed earlier). Thus, the “-5.8%” entry in the tech-savviness column for the age variable corresponding to PSSRAV. However, the age change also leads to positive enthusiasm increase and positive anxiety reduction sub-effects, leading to an overall positive ATE effect in the final column.

6.1 AV Interest Promotion

The first row panel of Table 8 provides the ATE effects with respect to AV interest promotion. As can be observed from the last column, the socio-demographic characteristics associated with age, gender, and employment have, by far, the highest overall ATE impact on AV interest. Specifically, older individuals, women, and those who are less educated are less interested in using AVs than their peers. The influence of all these socio-demographic characteristics on AV interest is primarily

mediated through enthusiasm (this is the value of the modeling framework adopted here, where we are able to identify the reasons why specific demographic groups are less likely or more likely to have specific behavioral intentions about AVs). This result suggests that, if the goal is to increase the interest in using AVs, policies should be directed at improving the positive affective emotion of enthusiasm toward AVs, as opposed to, for example, policies directed at increasing tech-savviness levels. A possible intervention measure to enhance enthusiasm would be to market the benefits and usefulness of AVs that are specific to older individuals, women, and the less educated. For example, AVs can be promoted as a means to avoid the difficulties of driving in old age, and also advertised as serving some of the same purposes as that of a much more expensive recreational vehicle. Given that older individuals may be the ones who are looking to retire and generally have more time (and buying power) on their hands, a renewed sense of adventure can be instilled and a new world of travel possibilities can be emphasized. Such targeted campaigns can mitigate concerns about new experiences and disruption in established habits. Among women, who typically are much more time-poor than men (especially if they have children; see Bernardo et al., 2015), the ability to use time productively in a hands-off environment can be highlighted as a way of allocating more time to pursue social-recreational activities of their choice. In addition, at least in the context of AV based ride-hailing services, which obviates the need for a driver, the resulting improved security can be promoted (women are known to have more concerns than men about a driver of a ride-hailing service not being adequately vetted, causing angst about personal safety and security; see Tarife, 2017). The lower levels of enthusiasm toward AVs among the less-educated is likely because of the concern that AVs would eliminate a large number of low-skilled job opportunities. Policies that promote affordable retraining programs for workers affected by automation may, to some extent, counteract the lack of enthusiasm among such individuals.

Lower income individuals are also less interested in using AVs, although the overall magnitude of this effect is relatively modest. This is because, while low income individuals have distinctly lower enthusiasm and higher levels of anxiety in relation to AVs, the direct effect on AV ridership interest (after controlling for the affective emotions, as discussed in Section 5.1.2) suggests that lower income individuals have a higher interest in riding in an AV (see earlier discussion about this effect). The affective and direct effects are in opposite directions, canceling out each other to a large extent. But the results still indicate that there is room to increase AV interest among low income individuals by increasing enthusiasm and decreasing anxiety. As

mentioned earlier, the unfavorable affective response of low-income individuals may be because they find it unlikely that they would be able to afford AV services. Therefore, if the premium on vehicles for having autonomous driving capabilities is not too high, even low-income individuals may become more interested in using AVs.

The ATE associated with VADA use results in a modest improvement in the interest in using AVs. On the other hand, tech-savviness has no effect on AV interest for any sociodemographic group. That is, experience with VADA can increase interest in AVs irrespective of tech-savviness levels and socio-demographic groups. Interestingly, experience with industrial robots does not play a role in AV interest, reinforcing the notion that the anthropomorphic nature of VADA may be at play here. An intervention based on exposure to other artificial intelligence based anthropomorphic technologies, including demonstrations of AVs themselves to the public in a controlled environment, may therefore increase AV interest.

6.2 Safety Perception Enhancement

As with the case of interest to ride AVs, the socio-demographic groups with the highest magnitude of ATE for PSSRAV are older individuals, women, and those who are less educated (see the last column of the lower level of Table 8). All of these socio-demographic groups consider sharing the road with AVs to be less safe than their respective peers. Again, the effects of these socio-demographic attributes are largely mediated through the affective emotions, particularly the latent construct of enthusiasm. Therefore, the policy measures mentioned earlier for promoting enthusiasm about AVs should also work to improve PSSRAV. Also, the relative magnitude of the mediating influence on PSSRAV through the anxiety latent construct is much higher for women than for the other socio-demographic groups. Marketing the safety benefits of AVs and retrofitting AVs with ample safety features may help in improving the affective reactions of women toward AVs. Women also generally have a lower PSSRAV relative to men because of not being as aware of AV developments as men (see the entry of “-6.0” in the “AV awareness increase” column corresponding to the “gender” row). So, AV information campaigns specifically targeted toward social groups that are typically dominated by women (such as book clubs, religious and spiritual groups, parent groups, performance and arts groups, and community associations; see Clark, 2000; Lowndes, 2004; Sedo, 2003) may be fruitful, as would be campaigns designed to increase AV awareness at work places/professional groups associated with women-dominant professions (such

as K-12 teachers, veterinarians, health information technicians, and public relations managers; see Rocheleau, 2017).

The tech-savviness effects in Table 8 for PSSRAV are interesting, and, as explained earlier, indicate that demographic groups that are more tech-savvy have a lower PSSRAV. Thus, it is important that, even as agencies and industry/car manufacturers customize their AV awareness and development campaigns toward the general public, it is also important to provide deep technical information about AV technology for consumption by those who are tech-savvy, so that their questions and concerns may be better addressed and not lead to a lower PSSRAV. Overall, however, the results indicate that AV awareness and tech-savviness considerations are less important than interventions focused toward improving affective responses to AVs.

In terms of technology use variable effects on PSSRAV, the results in Table 8 are consistent with the discussions in Section 5.1.2. They also point to the ability of our framework to disentangle tech-savviness effects from the technology experiential effect. Specifically, the results indicate that a positive experience with VADAs and the absence of a negative experience with industrial robots are far more important to improve PSSRAV than information campaigns to improve tech-savviness (for example, for the age variable, the tech-savviness ATE effect may be computed as 0.011, while the positive VADA experience effect is about three times larger and the negative industrial robot effect is about four times larger; similar substantial effectiveness scale factors are obtained for the technology experience ATE effects relative to the tech-savviness ATE for other socio-demographic groups). That is, the actual experiential pathway effect of technology use dominates over the tech-savvy lifestyle effect in the context of improving PSSRAV, clearly identifying treatment measures that increase positive experiences (and/or the absence of negative experiences) with specific technologies as a more effective approach than campaigns to enhance tech-savviness in the population. Overall, these results highlight the critical need not only to keep the public abreast of AV developments, but also ensure that initial experiences and demonstrations with AVs explicitly highlight the value of such vehicles in terms of safety capabilities, reliability, and ease of use. Holding demonstrations is not adequate; effective demonstrations without hiccups are needed to instill safety confidence. At least in the context of PSSRAV, the results suggest that poor AV demonstrations are likely to be worse than having no AV demonstrations at all.

6.3 Lowering Support for AV Regulation

The ATEs in Table 9 indicate that increasing the interest to ride in AVs and improving PSSRAV (especially the latter) represent the best policy instruments to reduce support for regulations (see the last two rows of Table 9). Customized interventions directed toward specific demographic groups to increase enthusiasm and decreasing anxiety, and thereby, increasing AV interest and PSSRAV, therefore, are the most effective means to lower support for regulations. Such interventions are particularly likely to help broaden the geographic extent of acceptance of AV operations in the public arena (as can be discerned from the higher magnitudes of effects for the regulation corresponding to “area restrictions”). The substantial impact of PSSRAV on AV regulation also underscores the importance of having companies that test AVs on public roads publicize the performance of these vehicles and the measures they have taken to ensure safety of others on the road. Thoughtful testing, design, and planning that, even if it cannot anticipate all edge cases, ensures that safety is not substantially degraded under any circumstance, is critical. Also of note is that the ATE of PSSRAV is higher than the ATE of the intent to ride AVs. Thus, to soften the demand for AV regulations, it would be better to publicize the specific safety benefits of AVs to the general public than to publicize the general benefits of AVs to the specific segment of the public that is likely use AVs.

Interestingly, tech-savviness too has a sizable direct effect on lowering support for AV regulations, unlike the relatively low to zero tech-savviness effect on AV interest and PSSRAV. That is, while campaigns to enhance tech-savviness levels (especially directed toward older adults and individuals with low education levels, low income, and the unemployed) may not yield substantial benefits in terms of increasing interest in personal AV use and PSSRAV, they are likely to prove quite effective in the context of softening public stance toward strict AV operating regulations and restrictions. In this regard, research in the information science literature (see, for example, Alhakami and Slovic, 1994; Frewer et al., 2011) suggests that tech-savviness campaigns should not simply be about providing passive knowledge on technology, but emphasize the value and benefits customized to the current lifestyles and habits of individuals. This brings up the broader issue of the critical need to fuse technological “geek” with human social considerations in technology dissemination campaigns with the aim of (1) underscoring the compatibility of technology within the context of current living, and (2) providing consistency in people’s beliefs and reducing the cognitive dissonance between risks and benefits. Tech-savviness campaigns that

do not underplay technology challenges, but clearly project the substantial user/social benefits relative to the minimal risk of AVs, are likely to be more effective in softening public stance toward AV regulations than broad-brushed technical and technology discourses.

Finally, in the context of AV regulations, older individuals, women, and those who are employed are more likely to support AV regulations, beyond any indirect effects of these variables through their impacts on AV interest and PSSRAV. The same approach as discussed above for tech-savviness campaigns, but targeted and customized to these specific demographic groups, may pay good dividends in softening AV regulation stances.

7 CONCLUSIONS

As the testing of AVs on public roads ramps up, and as services based on these vehicles are gradually introduced into the market, it becomes important to understand not only the public interest to use AVs but also the perceived safety of allowing AVs on public roads. Using a joint latent construct-based formulation, this study has modeled the interest in using AVs, the perceived safety of sharing the road with AVs (PSSRAV), and the preferences for three proposed AV regulations. The affective attributes of enthusiasm and anxiety associated with AV development, and the lifestyle attribute of tech-savviness, serve as the stochastic latent constructs in our framework. In addition to a psychological basis for considering these constructs, the constructs serve as a parsimonious approach to jointly model the multiple endogenous outcomes of interest. Such a joint model fits the data better than a model that considers the outcomes as being independent.

The model estimation results are translated into average treatment effects that provide insights for policy actions and interventions that are likely to make individuals feel safer to share the road with AVs and less likely to favor regulations that restrict the use of AVs. Some important general conclusions from our study are the following: (1) affective responses to AVs are critical determinants of AV awareness, interest in riding AVs, PSSRAV, and views regarding AV regulations; interventions targeted and customized to specific demographic groups, and aimed at improving enthusiasm and reducing anxiety about AVs, are likely to be far more effective (in promoting interest in AV use, enhancing PSSRAV, and lowering support for AV regulations) than those based on elevating tech-savviness levels or presenting positive technology use experiences (2) the actual experiential pathway effect of technology use dominates over the tech-savvy lifestyle

effect in the context of improving PSSRAV; treatment measures that aim to increase good experiences with VADA technologies and reduce poor experiences with industrial robots are likely to be more effective in improving PSSRAV than campaigns to elevate tech-savviness levels, (3) agencies desirous of reducing public support for strict AV regulations need to primarily focus on improving public perceptions of safety related to sharing roads with AVs, which then implies again the need for interventions that promote the positive affective emotion of enthusiasm and reduce the negative affective emotion of anxiety; interestingly, tech-savviness too has a sizable direct effect on lowering support for AV regulations, unlike the relatively low to zero tech-savviness effect on AV interest and PSSRAV.

More generally, the results point to the need for effective citizen awareness and safety information/demonstration campaigns about AVs. Service providers and public agencies need to be cognizant of the demographic and lifestyle/affective emotion considerations shaping AV safety perceptions and regulations, and use these insights to inform customized intervention strategies targeted toward specific demographic groups. In particular, there is a need not only to focus on technological and other infrastructure components of AV development, but also recognize the socio-technical considerations and human-related factors of the end-users. Our findings should be of substantial interest to AV proponents, car manufacturers, public agency leaders, and technology and infrastructure providers in the context of accelerating AV testing on public roads and eventually introducing AVs within a safe and minimally regulated public arena.

Of course, there is substantial room for additional research in this socio-technical area, including considering the influence of other technology use effects (such as use and experience of currently existing partial autonomous driving features, such as automatic cruise control or Tesla's autopilot feature). Also, extending the current analysis to include a richer set of household-level demographic variables (in addition to the individual-level demographic variables used in the current paper) would be valuable (unfortunately, the ATP data used for analysis in the current paper collected information only on individual demographics and not on household demographics). Including such a richer set of technology use and household demographic variables can provide additional insights on the relative contributions of demographics, affective emotions, and technology use effects on the interest to ride in an AV, PSSRAV, and regulation-related perceptions. Nonetheless, we believe the shifts in the relative contributions due to these improved

specifications will not be substantial, and that the current paper provides good order-of-magnitude effects of the different relative contributions.

To conclude, and most importantly, there is a need for greater emphasis in the transportation discipline on investigating the influence of human affective emotions and behavioral intentions on AV acceptance, testing, and eventual adoption.

ACKNOWLEDGEMENTS

This research was partially supported by the U.S. Department of Transportation through the Data-Supported Transportation Operations and Planning (D-STOP) Tier 1 University Transportation Center (Grant No. DTRT13GUTC58). The authors would like to express their gratitude to the researchers at the Pew Research Center for collecting and making publicly available the dataset used in this study and their prompt responses to the authors' questions regarding the dataset. The authors are grateful to Lisa Macias for her help in formatting this document. Two anonymous reviewers provided useful comments on an earlier version of this paper.

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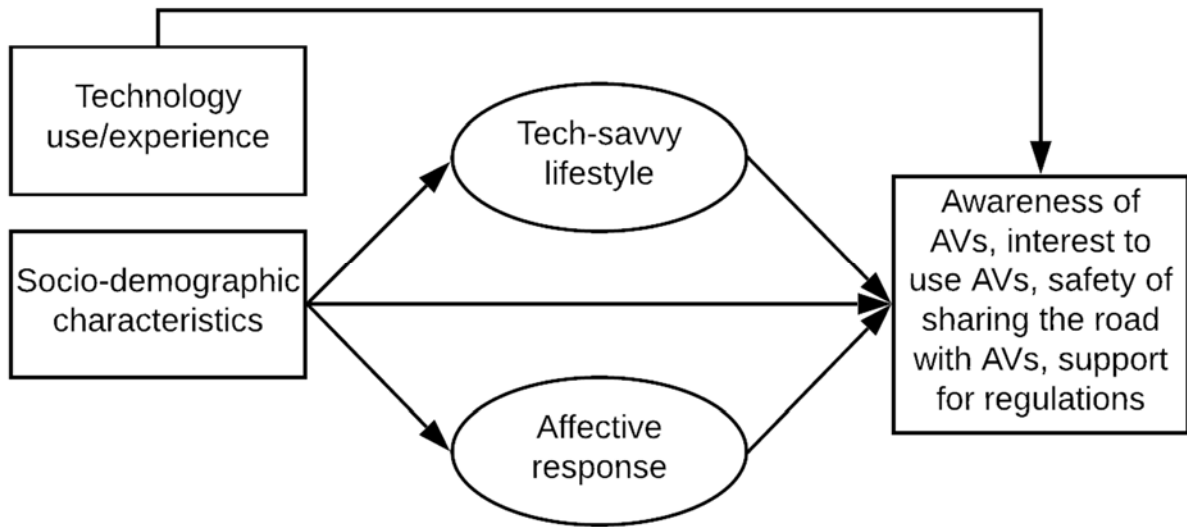
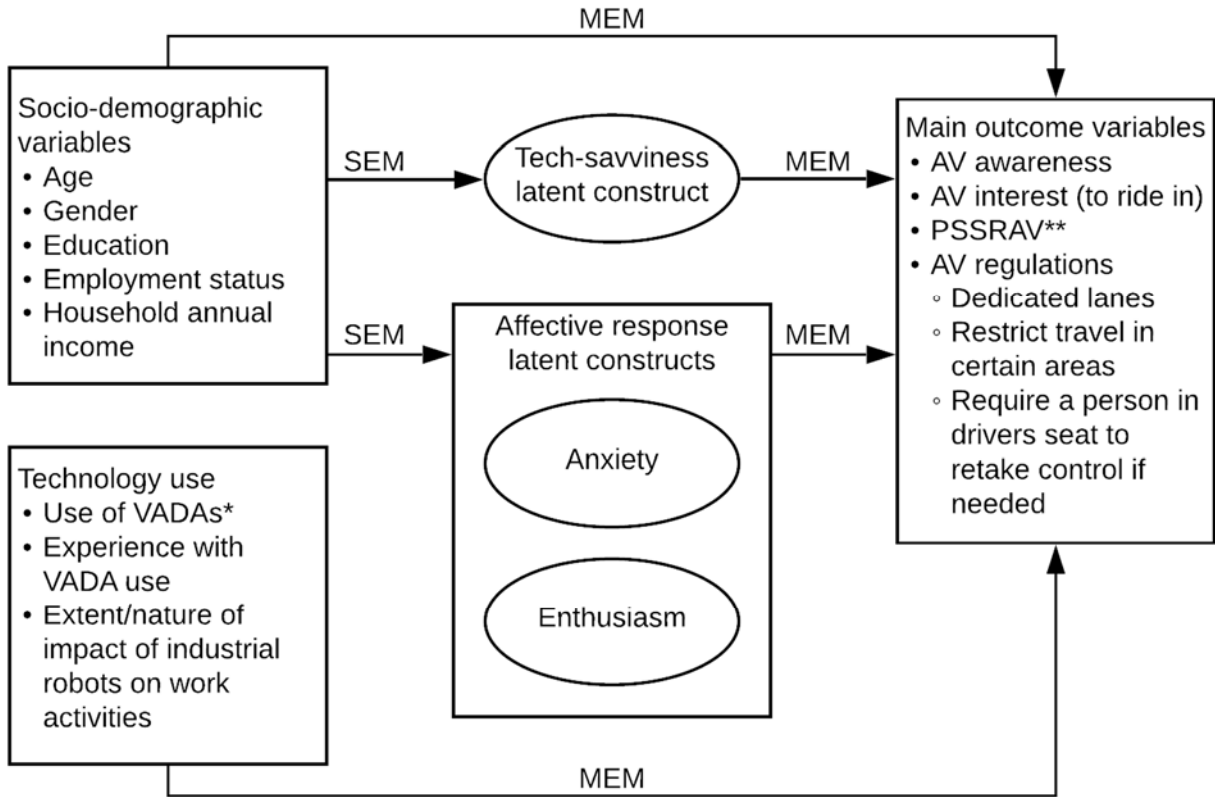


Figure 1. Conceptual Modeling Framework



* Voice Activated Digital Assistant (VADA)

** Perceived safety of sharing the road with AVs (PSSRAV)

Figure 2. Methodological Framework

Table 1. Comparison of the Sample Socio-Demographic Characteristics with that of the U.S. Adult Population

| Variable | ATS Sample | US Census, 2019 |
|------------------------------------|-------------------|------------------------|
| Age | | |
| 18-29 | 11.2% | 21.7% |
| 30-49 | 28.9% | 33.6% |
| 50-64 | 32.0% | 25.4% |
| 65+ | 27.9% | 19.3% |
| Sex | | |
| Male | 49.9% | 48.7% |
| Female | 50.1% | 51.3% |
| Education | | |
| High school or less | 14.5% | 40.5% |
| Some college or Associate's degree | 31.5% | 31.1% |
| Bachelor's and beyond | 54.0% | 28.4% |
| Employment status | | |
| Employed | 61.2% | 60.1% |
| Unemployed | 38.8% | 39.9% |

Table 2a. Sample Shares of Variables Used Only as Indicators of Affective Response and Tech-Savviness

| Variable | Ordered category 1 | | Ordered category 2 | | Ordered category 3 | | Ordered category 4 | |
|---|-------------------------|-------------|-------------------------------|-------------|-----------------------|------|--------------------|------|
| | Category name | % | Category name | % | Category name | % | Category name | % |
| Tech-savviness indicators | | | | | | | | |
| Frequency of computer use | Never / Almost never | 3.6 | Some days | 9.2 | Most days | 14.7 | Everyday | 72.5 |
| Frequency of internet use | Less than once a day | 11.8 | Few times / around once a day | 25.4 | Many times a day | 62.8 | | |
| Uses laptop | No | 26.5 | Yes | 73.5 | | | | |
| Uses tablet or e-book reader | No | 48.8 | Yes | 51.2 | | | | |
| Used voice activated digital assistant in smart devices (VADAs) | No | 23.6 (48.2) | Yes | 25.4 (51.8) | Question not asked | 51.0 | | |
| Enthusiasm about the development of AVs | Not at all enthusiastic | 19.0 | Not too enthusiastic | 38.7 | Somewhat enthusiastic | 29.6 | Very enthusiastic | 12.7 |
| Worried about the development of AVs | Not at all worried | 11.6 | Not too worried | 37.1 | Somewhat worried | 39.9 | Very worried | 11.4 |

Table 2b. Sample Shares of Technology-Use Variables

| Variable | Ordered category 1 | | Ordered category 2 | | Ordered category 3 | | Ordered category 4 | |
|---|--------------------|----------------|--------------------|----------------|--------------------|----------------|--------------------|------|
| | Category name | % | Category name | % | Category name | % | Category name | % |
| <i>(Subsample for which questions on digital assistants were asked)</i> | No | 51.0 | Yes | 49.0 | | | | |
| Used voice activated digital assistant (VADA) in smart devices | No | 23.6 (48.2) | Yes | 25.4 (51.8) | Question not asked | 51.0 | | |
| How often VADAs respond accurately | Not very often | 3.5 (13.9) | Some of the time | 10.5 (41.4) | Most of the time | 11.4 (44.7) | Question not asked | 74.6 |
| Impact of industrial robots at work | Negative | 6.0 (9.8) | No impact | 36.8 (60.2) | Positive | 18.4 (30.0) | Question not asked | 38.8 |

Table 3. Sample Shares of Behavioral Intent Variables

| Variable | Ordered category 1 | | Ordered category 2 | | Ordered category 3 | | Ordered category 4 | |
|--|--------------------|------|--------------------|------|--------------------|------|--------------------|------|
| | Category name | % | Category name | % | Category name | % | Category name | % |
| Seen or heard about efforts to develop AVs (AV awareness) | Nothing at all | 3.4 | A little | 55.2 | A lot | 41.4 | | |
| Interested in riding AVs (AV interest) | No | 52.3 | Yes | 47.7 | | | | |
| Perceived safety of sharing road with autonomous passenger vehicles (PSSRAV) | Not safe at all | 13.6 | Not too safe | 33.0 | Somewhat safe | 39.9 | Very safe | 13.5 |
| Sentiment toward AV regulations | | | | | | | | |
| Requiring AVs to travel in dedicated lanes | Strongly oppose | 3.5 | Oppose | 13.7 | Favor | 38.7 | Strongly favor | 44.1 |
| Restricting AVs from traveling near certain areas, such as schools | Strongly oppose | 5.2 | Oppose | 29.1 | Favor | 35.3 | Strongly favor | 30.4 |
| Requiring AVs to have a person in the driver's seat who could take control | Strongly oppose | 2.0 | Oppose | 10.7 | Favor | 36.9 | Strongly favor | 50.4 |

Table 4. Estimation Results for Tech-Savviness and Affective Response Latent Constructs

| Variable | Tech-savviness | | Enthusiasm | | Anxiety | |
|--------------------------------------|----------------|---------|------------|---------|---------|---------|
| | Coef. | t-stat | Coef. | t-stat | Coef. | t-stat |
| Age (Base: 50+) | | | | | | |
| 18 – 29 | 0.667 | 7.07 | 0.712 | 10.99 | -0.239 | -3.02 |
| 30 – 49 | 0.528 | 8.37 | 0.342 | 7.74 | -0.152 | -2.84 |
| Female | -- | -- | -0.363 | -9.24 | 0.444 | 9.23 |
| Education (Base: Bachelors or above) | | | | | | |
| High school or less | -1.166 | -14.88 | -0.518 | -8.39 | 0.292 | 4.08 |
| Some college or associate’s degree | -0.551 | -9.38 | -0.296 | -6.76 | 0.154 | 3.00 |
| Employed | 0.584 | 10.57 | -- | -- | -- | -- |
| Annual HH income less than \$75,000 | -0.533 | -9.68 | -0.246 | -5.71 | 0.192 | 3.95 |
| Correlation between error terms | | | | | | |
| Tech-savviness | 1.000 | (fixed) | | | | |
| Enthusiasm | 0.296 | 10.48 | 1.000 | (fixed) | | |
| Anxiety | -0.259 | -7.62 | -0.674 | -16.20 | 1.000 | (fixed) |

Table 5. Estimation Results for AV Awareness, Interest in Using AVs and Perceived Safety of Sharing the Road with AVs

| Variable Category | Variable | AV Awareness (“Nothing at all” to “A lot”) | | AV Interest (“Yes”: Base is “No”) | | PSSRAV (“Not safe at all” to “Very safe”) | |
|---------------------------|--|--|---------|-----------------------------------|---------|---|---------|
| | | Coef. | t-stat | Coef. | t-stat | Coef. | t-stat |
| Latent construct effects | Tech-savviness | 0.117 | 3.43 | -- | -- | -0.107 | -2.63 |
| | Enthusiasm | 0.538 | 7.11 | 2.232 | 10.21 | 1.321 | 11.42 |
| | Anxiety | 0.343 | 4.50 | -0.528 | -3.78 | -0.826 | -5.86 |
| Socio-demographic effects | Age (Base: 50+) | | | | | | |
| | 18 – 29 | -0.525 | -6.22 | -- | -- | -- | -- |
| | 30 – 49 | -0.393 | -6.61 | -- | -- | -- | -- |
| | Female | -0.535 | -10.23 | -- | -- | -- | -- |
| | Education Level: High School or less | -0.174 | -2.46 | -- | -- | -0.345 | -3.90 |
| | Employed | -0.123 | -2.30 | -- | -- | 0.227 | 3.41 |
| | Annual HH income less than \$75,000 | -0.125 | -2.33 | 0.212 | 2.11 | -- | -- |
| Technology-use effects | <i>Does not belong to subsample for which questions on VADA use was asked</i> | | | 0.055 | 0.47 | 0.031 | 0.53 |
| | Used VADAs (Yes) | -- | -- | 0.365 | 2.85 | -- | -- |
| | VADA experience: Digital assistant responds accurately <u>most of the time</u> | -- | -- | -- | -- | 0.201 | 2.14 |
| | Impact of industrial robots at work (Base: No impact) | | | | | | |
| | Positive | -- | -- | -- | -- | -- | -- |
| Negative | -- | -- | -- | -- | -0.278 | -2.72 | |
| Recursive effects | Heard of AV developments: A lot | -- | -- | -- | -- | 0.272 | 3.78 |
| Constants/ Thresholds | Thresholds between ordered levels | | | | | | |
| | 1 2 | 0.000 | (fixed) | 0.000 | (fixed) | 0.000 | (fixed) |
| | 2 3 | 2.366 | 39.53 | | | 2.329 | 24.30 |
| | 3 4 | | | | | 5.144 | 27.20 |
| | Constant | 2.779 | 32.73 | 0.509 | 3.44 | 3.031 | 20.63 |

Table 6. Estimation Results for Regulatory Preferences

| Variable category | Variable | Support for regulation (Strongly oppose - Strongly favor): | | | | | |
|---------------------------|---|---|---------|-------------------|---------|----------------|---------|
| | | Dedicated AV lanes | | Area restrictions | | Back-up driver | |
| | | Coef. | t-stat | Coef. | t-stat | Coef. | t-stat |
| Latent construct effects | Tech-savviness | -0.206 | -7.67 | -0.242 | -9.32 | -0.221 | -8.32 |
| Socio-demographic effects | Age < 30 | -0.147 | -2.29 | -- | -- | -- | -- |
| | Female | 0.343 | 7.26 | 0.128 | 2.78 | 0.313 | 6.74 |
| | Employed | 0.204 | 3.82 | 0.170 | 3.23 | 0.218 | 4.08 |
| Recursive effects | Interest in riding AVs: Yes (Base: No) | -0.261 | -4.11 | -0.414 | -6.38 | -0.187 | -3.10 |
| | Perceived safety of sharing the road with AVs (Base: Not safe at all) | | | | | | |
| | Not too safe | -0.181 | -2.32 | -0.283 | -4.10 | -0.471 | -5.74 |
| | Somewhat safe | -0.463 | -5.34 | -0.715 | -8.66 | -0.832 | -9.35 |
| | Very safe | -1.040 | -9.88 | -1.371 | -12.96 | -1.299 | -12.31 |
| Constants/ Thresholds | Thresholds between ordered levels | | | | | | |
| | 1 2 | 0.000 | (fixed) | 0.000 | (fixed) | 0.000 | (fixed) |
| | 2 3 | 0.998 | 20.31 | 1.472 | 31.33 | 1.019 | 18.18 |
| | 3 4 | 2.292 | 40.33 | 2.639 | 51.04 | 2.357 | 37.24 |
| | Constant | 2.327 | 28.94 | 2.567 | 34.27 | 2.822 | 32.21 |

Table 7. Comparison of Disaggregate Goodness-of-fit Measures Between GHDM and IOP Models

| | GHDM | IOP |
|---|-------------|------------|
| No. of observations | 3541 | 3541 |
| No. of parameters | 102 | 74 |
| Average probability of correct prediction | 0.0119 | 0.0089 |
| Predictive log-likelihood at convergence $L(\hat{\theta})$ | -18943.19 | -19878.53 |
| Predictive log likelihood of base (independent market share) model $L(c)$ | -21828.15 | -21828.15 |
| Predictive Adjusted Likelihood Ratio Index | 0.1282 | 0.0866 |

Table 8. Socio-Demographic and Technology Use ATE Effects on AV Ridership and PSSRAV

| Variable | Base Level | Treatment Level | % Contribution by mediation through | | | | % Direct Effect | Overall ATE |
|---|--------------------|---------------------|-------------------------------------|---------------------|-------------------|-----------------------|-----------------|-------------|
| | | | Tech-savviness Increase | Enthusiasm Increase | Anxiety Reduction | AV Awareness Increase | | |
| Interest in riding AVs: Yes (Base is No) | | | | | | | | |
| <i>Socio-demographic</i> | | | | | | | | |
| Age | 50+ | 18-29 | 0.0 | 92.6 | 7.4 | 0.0 | 0.0 | 0.229 |
| Gender | Male | Female | 0.0 | -77.6 | -22.4 | 0.0 | 0.0 | -0.141 |
| Education | Bachelors or above | High school or less | 0.0 | -88.2 | -11.8 | 0.0 | 0.0 | -0.175 |
| Employment Status | Unemployed | Employed | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.000 |
| Income | ≥ \$75,000 | < \$75,000 | 0.0 | -63.6 | -11.8 | 0.0 | 24.6 | -0.059 |
| <i>Technology experience</i> | | | | | | | | |
| VADA | No experience | Positive experience | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 | 0.049 |
| Industrial robots | Negative impact | No Negative impact | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.000 |
| PSSRAV: Somewhat Safe/Very Safe (Base is Not at All Safe/Not Too Safe) | | | | | | | | |
| <i>Socio-demographic</i> | | | | | | | | |
| Age | 50+ | 18-29 | -5.8 | 77.0 | 16.1 | -1.1 | 0.0 | 0.174 |
| Gender | Male | Female | 0.0 | -53.3 | -40.7 | -6.0 | 0.0 | -0.154 |
| Education | Bachelors or above | High school or less | 8.6 | -47.6 | -16.8 | -3.0 | -24.0 | -0.204 |
| Employment Status | Unemployed | Employed | -21.2 | 0.0 | 0.0 | -1.7 | 77.1 | 0.027 |
| Income | ≥ \$75,000 | < \$75,000 | 7.2 | -69.6 | -20.2 | -3.0 | 0.0 | -0.077 |
| <i>Technology experience</i> | | | | | | | | |
| VADA | No experience | Positive experience | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 | 0.033 |
| Industrial robots | Negative impact | Positive impact | 0.0 | 0.0 | 0.0 | 0.0 | 100.0 | 0.047 |

Table 9. ATE Effects on the AV Regulation of Dedicated Lanes

| Variable | Base Level | Treatment Level | ATE on Favor/Strongly Favor Regulation (Base is Strongly Oppose/Oppose Regulation) | | |
|--------------------------|-----------------|-----------------|--|-------------------|----------------|
| | | | Dedicated AV lanes | Area restrictions | Back-up driver |
| Tech-savviness | 25th percentile | 75th percentile | -0.048 | -0.079 | -0.041 |
| <i>Socio-demographic</i> | | | | | |
| Age | 50+ | 18-29 | -0.033 | 0.000 | 0.000 |
| Gender | Male | Female | 0.074 | 0.038 | 0.054 |
| Employment Status | Unemployed | Employed | 0.044 | 0.050 | 0.039 |
| <i>Behavioral intent</i> | | | | | |
| AV Ridership | No | Yes | -0.056 | -0.128 | -0.033 |
| PSSRAV | Not safe | Safe | -0.156 | -0.292 | -0.140 |