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Investigating Adoption Behavior of Owned and Shared Autonomous Vehicles: An Updated Technology Acceptance Model

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INVESTIGATING ADOPTION BEHAVIOR OF OWNED AND SHARED AUTONOMOUS VEHICLES: AN UPDATED TECHNOLOGY ACCEPTANCE MODEL

A Thesis

by

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ABSTRACT

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Transportation systems will be likely transformed by the emergence of autonomous vehicles (AVs), either owned privately or used in a shared system (SAVs), which promise for safe, convenient, and efficient mobility, to name a few benefits to society. The manifestation of (S)AV benefits, however, is still dubious due to the observed public reluctance, or at best neutrality, towards (S)AVs, especially SAVs. The public's perception towards these innovations is still unclear, therefore, a gap remains in the analysis of individuals' behavioral intention (BI) to use AVs and SAVs. To fill that gap, this study uses a behavioral psychology method. Specifically, an updated technology acceptance model (TAM) is proposed which includes the ad-hoc latent constructs (i.e., perceived usefulness, BI to use AVs, and BI to use SAVs) as well as new latent constructs explaining perceived concern about (S)AV safety, pro-drive attitude, green travel pattern, and shared-mobility experience. The proposed TAM is empirically estimated on dataset of the California Vehicle Survey collected by California Energy Commission in 2019. The study findings reveal the positive tendency of individuals who experience shared mobility services (e.g., Uber and Lyft) towards both AVs and SAVs. In addition, pro-drive is a barrier hindering (S)AV acceptance, especially SAVs. To capture heterogeneity of the individuals, the findings are further analyzed by connecting individuals' tendencies to each latent construct to their socio-economic attributes. Insights from this study can be used in future policy decisions and for future research.

DEDICATION

The completion of my thesis studies would not have happened without the encouragement and support from my family, friends, and colleagues. Through stressful and difficult times, they were present to motivate and support me in all means to accomplish and complete this degree. Thank you for always being by my side, it means the world to me.

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INTRODUCTION

1.1 Motivation

The future of transportation systems is evolving with the emergence of two technological advances in conventional mobility — i.e., automated vehicles (AVs, or self-driving cars) and shared mobility (Cohen and Kietzmann, 2014; Alessandrini et al., 2015; Elliott et al., 2019). AVs are capable of operating without any human interaction, and thus can provide safer travels, and less traffic congestion and fuel emissions, to name a few benefits (Fagnant and Kockelman, 2015; Greenblatt and Shaheen, 2015; Katrakazas et al., 2015). Shared mobility, on the other hand, is a new mode of transportation, gaining recognition with some of its popular on-demand services such as carsharing, ridesharing, and ride-hailing (Agatz et al., 2012; Nie, 2017; Shaheen et al., 2009). These on-demand services are cost-efficient services, shared among users by transporting multiple individuals at once with optimized routing (Fagnant and Kockelman, 2015; Panagiotopoulos and Dimitrakopoulos, 2018; Shaheen et al., 2016).

Shared AVs (SAVs) are the conflation from both coexistent services, and if accepted, can arguably promise solutions to the barriers disrupting the transportation system. By exploiting benefits of both AV and on-demand mobility, SAVs can potentially, for instance, improve public transit through serving as first/last mode and provide independent mobility for individuals unfit for driving (e.g., the elderly and people with disabilities) (Meyer et al., 2017; Sparrow and Howard, 2017). Presumably, SAVs possess a greater advantage over AVs, by having greater demand and appeal versus private ownership of AVs (Fagnant et al., 2016; Fagnant and Kockelman, 2014; Krueger et al., 2016). However, with the possible manifestation of (S)AVs, there are still questions about how the public will perceive and react to AVs and SAVs in the future.

Despite the projected benefits mentioned above, the public is still reluctant towards (S)AVs (Abraham et al., 2017; Liljamo et al., 2018; Narayanan et al., 2020; Xu et al., 2018) mostly due to rather psychological than technological factors (Liu et al., 2019; Noy et al., 2018; Xu et al., 2018). These hesitations from the potential consumers may postpone the penetration of (S)AVs into the market and in turn limit AV benefits. In order to advance the existing understanding of factors hindering the public to accept and use (S)AVs, the present research contributes to the relevant literature by proposing an updated technology acceptance model (TAM). The study results can differentiate among multiple transportation services, considering all-purpose daily travels, to help target individual characteristics which can potentially drive public interest.

1.2 Background

A large body of the existing literature with the *psychological* perspective explores acceptance of technology by connecting individuals' acceptance behavior to their traits, attitudes, and preferences. Application examples are in communication systems (e.g., Gefen and Straub, (1997)), the internet (e.g., Lederer et al., (2000)), mobile phone (e.g., Renaud and Van Biljon, (2008)), and computers (e.g., Teo et al., (2008)). On the acceptance behavior of (S)AVs, a growing body of literature adopts this perspective to build models based on the relevant theories. For instance, TAM (Davis et al., 1989) explains usage behavior across a range of technological systems based on two main beliefs (e.g., Lee et al., (2019), Panagiotopoulos and Dimitrakopoulos, (2018), Zhang et al., (2019), Theory of Planned Behavior (TPB, Ajzen, (1991)), explains human behavior with antecedents of attitudes, subjective norms, and behavioral control (e.g., Buckley et al., (2018)), Unified Theory of Acceptance and Use of Technology (UTAUT, (Venkatesh et al., 2003)) consists of four predictors (i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions) as the foundation for users' behavioral intentions (e.g., Madigan et al., (2017), (2016)). Also, UTAUT2 (Venkatesh et al., 2012) updates UTAUT by adding 3 constructs including hedonic motivation, price value, and habit (e.g., Yuen et al., (2020)) and TAM2 (Venkatesh and Davis, 2000) updates TAM by adding theoretical constructs social influence and four cognitive instrumental determinants (e.g., Zhang et al., (2020)).

Derived from the Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1975), the initial TAM is proposed by Davis et al. (1989) to investigate users' acceptance of information systems which consists of three specific beliefs including PU, perceived ease of use (PEU), and BI to use the technology. PU is defined as a consumer's perception in which they believe using the particular technology will enhance their performance. PEU refers to the degree in which the consumer perceives the use of a technology system will be easy to use and therefore, free from effort (Davis et al., 1989). Lastly, behavioral intention (BI) refers to the individuals' intention to use a particular system based on their attitude and PU, which can translate into actual usage behavior (Davis et al., 1989).

The main objective of TAM is to identify factors on internal beliefs, attitudes, perceptions, and intentions, and therefore, determine if there is a theoretical relationship among these determinants to explain user behavior (Davis et al., 1989). TAM attempts to not only explain the observed behavioral intention to use a technology by explanatory variables but to also predict the expected intention. Venkatesh and Davis (1996) extend the original TAM where PU and PEU directly influence BI without the necessity of implementing attitude on the constructs. The updated framework is widely used in many studies to analyze and understand a consumer's motives for future adoption of AVs and SAVs.

However, studies on (S)AV acceptance are inconsistent when considering the relationship between the two latent constructs, i.e., PU and PEU. Few studies report that the relationship between both is significant while others do not find PEU to affect PU nor BI (Buckley et al., 2018; Lee et al., 2019). PEU is weak or irrelevant due to two major reasons according to Choi and Ji (2015) and Lee et al. (2019). First, BI relies heavily on PU rather than PEU since automated vehicles are already easy to use. Second, the inconsistency of PEU is based on the latent constructs used to predict BI for that particular model, making it a non-significant predictor (Madigan et al., 2017). Regardless of this, a few studies continue using the original TAM framework, while others modify TAM with the addition of new latent constructs or removal of PEU from the model.

1.2.1 The existing studies using Technology Acceptance Model

To explain and predict AV acceptance, the existing studies extend the original TAM. For instance, Panagiotopoulos and Dimitrakopoulos (2018) extend the original TAM by adding trust and social influence latent constructs. By estimating the proposed model on a sample dataset of 483 individuals, the results reveal the positive impact of all determinants on individuals' BI. Similarly, Zhang et al. (2019) propose another updated TAM by including latent constructs explaining trust, perceived safety risk, and perceived privacy risk. They hypothesized that the latent constructs have a direct relationship to trust, with trust being a key determinant to BI. Estimated on a sample dataset of sixteen respondents, the results show that not all latent constructs have a significant effect on AV acceptance as expected, with trust not making the strongest impact as hypothesized. Also, Choi and Ji (2015) extend TAM by adding seven latent constructs (i.e., trust, system transparency, technical competence, situation management, perceived risk, external locus control, and sensation seeking). The results revealed that not all latent influence BI to use AVs, however, trust is the strongest determinant. An experimental study by Xu et al. (2018) use TAM as a foundation and include perceived safety and trust latent constructs. The authors conclude that all determinants are direct predictors, with trust having a greater effect after individuals rode inside an AV. In common, all these studies use TAM as a foundation and extend it to fulfill their objective of exploring which latent constructs more influence AV acceptance. However, none of these extended models explore SAV acceptance, and as mentioned previously, this research contributes by analyzing SAV adoption by proposing an extended TAM.

Another common observation on existing studies is the repetitiveness of several latent constructs, with the difference of analyzing different observable factors (e.g., socio-economic characteristics). Besides the ad-hoc latent constructs, perceived trust and safety are the constructs most frequently analyzed. Although they prove to make a significant contribution towards influencing individuals' BI (Fraedrich and Lenz, 2016; Lee et al., 2019; Xu et al., 2018; Zhang et al., 2019; Zoellick et al., 2019), there need to be different approaches to further explore what other factors influence (S)AV adoption without repeating. A few studies follow a different path to develop distinctive models evaluating unique latent constructs such as social media (Panagiotopoulos and Dimitrakopoulos, 2018), attitudes towards (S)AVs (Hegner et al., 2019; Lee et al., 2019) and travel patterns (Lavieri et al., 2017; Nazari et al., 2018).

As mentioned above, there is a great importance of discovering new yet meaningful factors that can positively impact users' acceptance. The existing studies have developed their research based on existing gaps, yet many still emphasize the necessity of exploring shared mobility, specifically to investigate SAV acceptance (Bansal et al., 2016). To our knowledge, Lavieri et al. (2017), Nair et al. (2018), and Nazari et al. (2018) are the only existing studies considering travel behavior as a latent construct. Their findings reveal this construct to be a direct predictor of SAV acceptance. Driven by the limited research on shared mobility, the present study further explores that the latent construct travel behavior explains and predicts (S)AV acceptance. Moreover, several studies focus solely on SAV acceptance by approaching it with different psychological acceptance models. Yuen et al. (2020) combined two existing models (TPB and UTAUT2), based on eight significant predictors. For example, Acheampong and Cugurullo (2019) proposed four different theoretical models to explore how each one influences (S)AV acceptance by integrating socio-economic characteristics, individuals' perceptions, behavior control, and attitudinal factors (i.e., environment, technology, public transit, car ownership). Each model gave distinct results, however, all proved significant in predicting SAV adoption. Madigan et al. (2017) propose a UTAUT model to investigate users' acceptance towards automated public transport systems, which find the hedonic motivation as the strongest predictor. As an experimental study, Paddeu et al. (2020) explores how comfort and trust affect passengers when riding an SAV (i.e., shuttle). The study find trust an important predictor of perceived comfort, with a significant increase in trust after experiencing SAV use. These studies provide an extent to understanding determinants of SAV acceptance, however, there is still a great uncertainty due to the limited number of studies.

1.2.2 Effects of socio-demographic characteristics on (S)AV acceptance

According to the relevant review studies (Becker and Axhausen, 2017; Gkartzonikas and Gkritza, 2019a), most of the existing studies agree that AV acceptance is influenced by socio-economic attributes such as age (e.g., Choi and Ji (2015), Etezady et al. (2020), Hohenberger et al. (2016), and Hulse et al. (2018)), gender (e.g., Haboucha et al. (2017), Hegner et al. (2019), and

Sener et al. (2019)), educational attainment (e.g., Daziano et al. (2017), Gkartzonikas and Gkritza (2019b), and Liljamo et al. (2018)), and income (e.g., Bansal et al. (2016) and Kyriakidis et al. (2015)). These four attributes are the most commonly observed, having a significance towards characterizing insight on the individuals most likely to express interest in (S)AVs.

Also, several studies disagree on the role age partakes in (S)AV adoption. On one hand, older drivers more inclined towards accepting and trusting AVs due to access of enhanced mobility, especially for those unable to drive (Etezady et al., 2020; Gold et al., 2015; Li et al., 2019). In addition, young and elder drivers are drivers more inclined towards (S)AV acceptance, with a willingness to own or use in the near future (Becker and Axhausen, 2017a; Hohenberger et al., 2016; Silberg, 2013). Presumably, young drivers will favor AV ownership, while the elderly incline towards shared mobility (Nazari et al., 2018). On the other hand, a few studies observe a negative or neutral tendency from older drivers towards acceptance of (S)AVs (Haboucha et al., 2017; Lavieri et al., 2017; Liu, 2020; Molnar et al., 2018; Sener et al., 2019; Wang et al., 2020). This is due to their reluctance to adopt new habits, with preference to their accustomed way of driving. This suggests that young individuals could be the early adopters of (S)AVs (Hardman et al., 2019). Furthermore, Keszey (2020) reviews studies on BI to use AVs, emphasized future research should focus on additional variables "effectively differentiating between groups of users." The study mentions the importance of targeting distinct groups such as generational groups (i.e., Millennials, Generation Y, Baby Boomers) as new variables to assess its effectiveness on behavioral intentions. To provide and improve the present ambiguities, this study will observe age as generations instead to include a greater representative sample while identifying new variables to examine how their perspectives converge through later life stages.

Furthermore, gender plays a significant role in (S)AV adoption. Panagiotopoulos and Dimitrakopoulos (2018) find men expressed more enthusiasm and interest in using AVs. Lavieri et al. (2017) and Nazari et al. (2018) find men more inclined in AV ownership and use of SAVs, which could relate to males being more adventurous and less concerned with risk. Further, there appears to be a correlation between education and income (Gkartzonikas and Gkritza, 2019b). (S)AVs are favored by individuals with higher education due to existent familiarity with AVs or willingness to accept new technology and ideas (Haboucha et al., 2017; Liljamo et al., 2018). It is assumed that individuals with higher education have a greater income. Previous studies find education to be a positive attribute favoring the use of (S)AVs (Daziano et al., 2017). This study will take the initiative of exploring additional socio-economic attributes to explore their significance, if any, by analyzing employment, demographic region, and student classification.

1.3 The present study in context

By exploring BI to use AVs as well as SAVs, the first contribution is an in-depth understanding of the users' acceptance of AVs and SAVs. While there is the importance of investigating behavioral interest in AVs, it is crucial to give equivalent significance, if not greater, to user acceptance of SAVs. However, a limited number of the existing studies focus on SAV acceptance signifying an existent vast area of unknown understanding on SAV adoption (Bansal et al., 2016; Haboucha et al., 2017; Krueger et al., 2016). With the growing demand for shared services (i.e., Uber, Lyft) (Cohen and Kietzmann, 2014) and the emergence of AVs, it will be a matter of time before SAVs disrupt urban mobility. Hence, it is important to recognize factors (de)incline individuals towards SAVs (also concluded by Haboucha et al., (2017)). The second contribution is that whether individuals' travel behavior can be a significant predictor of BI to use (S)AVs in the future. To do so, two travel behavior latent constructs are defined in the modeling framework of this study including shared mobility and green mobility. Although there is a growing interest in behavioral mobility (Agatz et al., 2012; Molin et al., 2016), very few studies attempted to implement green travel patterns as a latent construct which is found to have an associated significant role (Lavieri et al., 2017; Nazari et al., 2018).

The updated TAM consists of the original framework, including perceived usefulness (PU) and behavioral intent (BI), in addition to two new latent constructs, including shared mobility (SME) and green mobility (GME) experience. The two latter constructs attempt to capture individuals' mobility patterns, which are rarely seen in relevant studies. This study will present its results from an existing dataset collected in the State of California, with a focus on respondents' perceptions of the ideology of autonomous vehicles. The results will interpret respondents' relative measures to each latent construct and interpret how it influences and characterizes their motives towards user acceptance of autonomous vehicles.

The structure of the paper follows with the next section discussing the existing studies on (S)AV acceptance. Chapter 2 the research methodology. Chapter 3 presents statistical analysis of the dataset used for the empirical estimation, followed by chapter 4 discussing and interpreting the empirical estimation results. Lastly, chapter 5 concludes a summary of the main findings and suggestions for future research.

CHAPTER II

METHODOLOGY

The present study updates the original TAM by including three sets of latent constructs explaining the perception of AV features, attitudes, and BI to use (S)AVs (Figure 1). The first set includes two latent constructs distinguishing individuals' BI to use AVs and SAVs built on three and two indicators, respectively. The second set includes three latent constructs capturing individuals' perception of AV features, explaining individuals' beliefs on (S)AVs functionality, safety concerns, and lastly their perceived emotions with driving. These constructs are built on four, one, and two indicators, respectively. The last set encompasses two latent constructs describing individuals' general attitudes on factors explaining their mobility patterns with shared and green commutes built on six and five indicators, respectively.

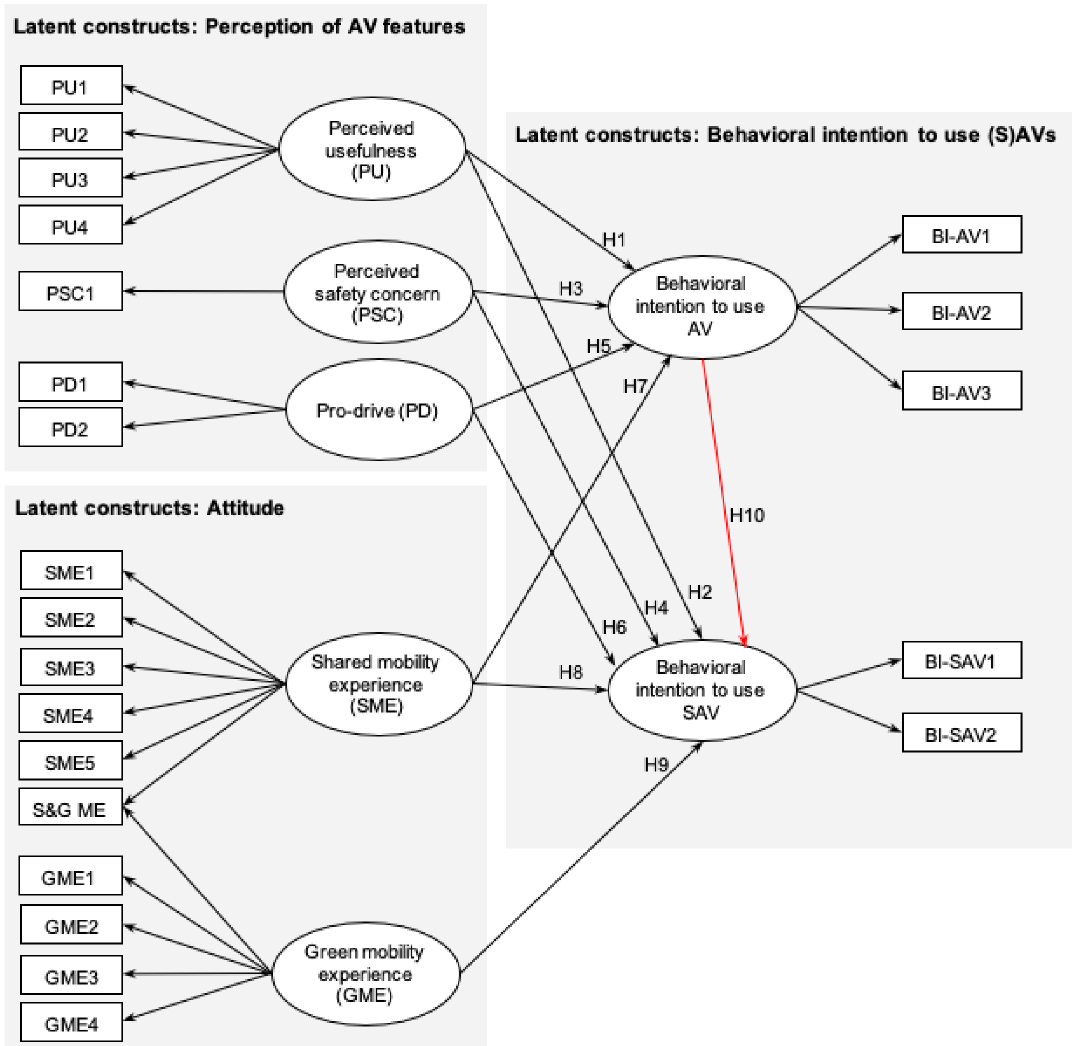


Figure 1: The updated technology acceptance model proposed in the present study

This study takes a different approach of investigating user acceptance, with the modeling framework (Figure 1) having the original standpoint but removing PEU due to insignificance. The model extends with four new latent constructs, including pro-drive (PD), perceived safety concern (PSC), and travel behavior, explaining shared mobility and green mobility experience. This study investigates behavioral interest in user acceptance of both AVs and SAVs to understand how these latent constructs affect a consumer's choice and preference. The rest of the section explains each set of the latent constructs with the hypotheses for each defined.

Table 1. Latent constructs and the corresponding indicators

Latent construct	Indicator	Definition of indicator
Behavioral intention to use (S)AV		
Behavioral intention to use AV (BI-AV)	BI-AV1	Which of the following best describes your familiarity with 'autonomous' or 'self-driving' (i.e., driverless) vehicles?
	BI-AV2	Consider your current situation with the vehicles your household now owns (if any), and imagine that driverless vehicles have become widely available for purchase. Which of the following scenarios best describes your household?
	BI-AV3	Overall, what would be your relative interest in owning a driverless vehicle versus using on-demand ride-hailing services?
Behavioral intention to use SAV (BI-SAV)	BI-SAV1	If on-demand driverless ride-hailing services were widely available today, which of the following best describes how your household would use these services and how it would impact the vehicle(s) you currently own?
	BI-SAV2	I would be likely to use shared driverless services (even at lower cost) because I would not want to share a vehicle with strangers.
Perception of AV features		
Perceived usefulness (PU)	PU1	I see a need for self-driving vehicles.
	PU2	I would reduce my time at the regular workplace and work more in the self-driving car.
	PU3	I would send an empty self-driving car to pick up/drop off my child.
	PU4	I would be able to travel more often even when I am tired, sleepy, or under the influence of alcohol/medications.
Perceived safety concern (PSC)	PSC1	I would accept longer travel times so the self-driving vehicle could drive at a speed low enough to prevent unsafe situations for pedestrians and bicyclists.
Pro-drive (PD)	PD1	A self-driving vehicle would enable me to enjoy traveling more (e.g., watch scenery, rest).
	PD2	I would miss the joy of driving and being in control.
Attitude		
Shared mobility experience (SME)		What is your experience with the following transportation options for trips in your local area?
	SME1	Rental car
	SME2	Ride-hailing (Uber/Lyft)
	SME3	Shared ride-hailing (UberPool/LyftLine)
	SME4	Carsharing (Car2Go, ZipCar)
	SME5	Peer-to-peer car rental (e.g., GetAround, Turo)
	S&G ME	Bikesharing (e.g., Bay Area Bike Share)
Green mobility experience (GME)		What is your experience with the following transportation options for trips in your local area?
	S&G ME	Bikesharing (e.g., Bay Area Bike Share)
	GME1	Public bus
	GME2	Light rail/tram/subway (e.g., BART, LA Metro)
	GME3	Commuter train (e.g. Amtrak, Caltrain)

Latent construct	Indicator	Definition of indicator
	GME4	Shared eBikes or eScooters (e.g., Jump)

2.1 Latent constructs explaining behavioral intention to use (S)AVs

Ever since Davis et al. (1989) introduced TAM over a decade ago, it has become a dominant model in investigating and explaining factors affecting users' acceptance of a specific technology (Marangunić and Granić, 2015). TAM predicts user motivation directly influenced by unobserved factors (i.e., latent variables) explaining perceptions and attitudes to determine users' predicted intent. BI refers to the degree in which individuals will use a system, in this case, AV systems (Davis et al., 1989). BI is an essential asset in the model, meditating the effects of the determinants to determine what motivates user acceptance.

2.1.1 Behavioral intention to AV

One of the main focuses of this paper is to find what determinants affect user's intentions to use AVs based on the latent constructs used in TAM. Existing AV studies have attempted to find and best explore what factors are relevant; however, none have used the same latent variables as this study. Behavioral intentions to use AVs (BI-AV) are built from four latent variables, with three determinants exploring perception of AV features and one determinant exploring attitudes, specifically the latent explaining shared mobility experience (SME). Moreover, if individuals are familiar with AVs, then they may be inclined in using SAVs (Lavieri et al., 2017).

H10: BI-AV positively influences consumers' BI-SAV.

2.1.2 Behavioral intention to SAV

Another important focus in this paper is to contribute to the existing gaps to understand and investigate SAV acceptance. With few studies exploring users' intent of SAVs, this study is a complementary addition with having all latent variables as direct determinants to explaining users' behavioral intention of SAV (BI-SAV) as noted in Figure 1. Acceptance of SAVs is critical in comprehending the future needs that are expected to arise from the current success with shared mobility and the advancement of AVs. Therefore, it is of best interest to start investigating what factors may influence consumers' to start approaching AVs, specifically SAVs due to higher projection rates in SAV usage (Greenblatt and Shaheen, 2015).

2.2 Latent constructs explaining perception of AV features

2.2.1 Perceived usefulness

As previously mentioned, PU is one of the fundamental principles of TAM and a direct predictor of BI. If the consumers can see potential in a particular technological system, then it can be used advantageously towards enhancing their job performance. Previous studies have found users' intentions to be better predictors of a system's usage rather than predictors such as "realism of expectations, motivational force, or user involvement" (Venkatesh and Davis, 1996). AVs can offer potential benefits to consumers as mentioned previously, including the flexibility of performing secondary tasks without requiring a driver's attention (Yoon and Ji, 2019).

H1: PU has a positive influence on consumers' BI to use AVs.

H2: PU has a positive influence on consumers' BI to use SAVs.

2.2.2 Perceived safety concern

There is a high risk when deciding to ride in a vehicle, with 94% of the accidents occurring due to human error (National Highway Traffic Safety Administration, 2008). According to Favarò et al. (2017), AVs can be a potential solution for dramatically reducing the rate of crashes. One of the main highlights prompting users to use AVs is the safety features enabled on them. Drivers placed in an (S)AV need to entrust their safety to the automated system, regardless of the risks and uncertainties associated with them. The greatest setback currently associated with (S)AVS are the concerns regarding safety and security issues, which may discourage the use of riding in them (Etezady et al., 2020). However, if consumers can trust an automated system, the possibility of demand for AVs is expected to rise. Ultimately, if consumers can perceive safety in AVs, it is safe to assume the same for the use of SAVs.

Perceived safety concern is defined as the degree to which individuals believe that the usage of an AV will affect their well-being, and be in an environment in which they can be relaxed and safe (Delbosc and Currie, 2012). According to Delbosc and Currie (2012), the inclusion of latent perceived safety concern in TAM leads to better predictions of BI and contributes positively towards the use of (S)AVs. In general, individuals who positively perceive safety concerns towards (S)AVs may have higher intentions to use them in the future.

H3: Latent perceived safety concern positively influences consumers' BI to use AVs.

H4: Latent perceived safety concern positively influences consumers' BI to use SAVs.

2.2.3 Pro-drive

A common desire frequently sought in consumer research is the ability to find pleasure or have joyful experiences. Psychological theories categorize this motivation for behavior into two categories: extrinsic and intrinsic motivation (Scott et al., 1988). Extrinsic motivation is defined as non-essential or an unnatural behavior for someone or something, and intrinsic motivation is the act or natural behavior of an activity due to genuine interest and enjoyment rather than reinforcement (Davis et al., 1992). Madigan et al. (2017) emphasized motivation as a key predictor in understanding consumer behavior although it has been understudied in existing AV literature.

Latent construct pro-drive reflects a similar motivation, specifically categorized as an intrinsic behavior since this latent defines individuals' natural enjoyment in the act of driving or having control of the wheel due to forthcoming pleasure (Davis et al., 1989). According to Steg (2005), driving creates emotions of “sensation, power, adventure, and pleasure.” Some drivers perceive driving as adventurous and pleasurable and may be reluctant in using (S)AVs if it means giving up the pleasure derived from driving. The ideology of AVs having the ability to operate without the requirement of a driver clearly has and creates a certain effect on individuals. The addition of pro-drive in TAM can explain how the performance of driving can positively or negatively influence an individual’s decision and attitude towards future use of (S)AVs.

H5: Latent pro-drive negatively influences consumers’ BI to use AVs.

H6: Latent pro-drive negatively influences consumers’ BI to use SAVs.

2.3 Latent constructs explaining attitudes

Personal lifestyle choices have a major effect on the propensity of using both AVs and SAVs. It is inferred that there is a direct relationship between travel behavior and interest in (S)AVs. According to Lavieri et al. (2017), travel behavior serves as an important factor when incorporating in latent constructs to make inferences about the magnitude it will have on transport choice behaviors. This study considers two key aspects: mobility on demand (MOD) and green travel behavior with a great interest in understanding how individuals' behavioral patterns influence potential interest in (S)AVs.

2.3.1 Shared mobility experience

Shared MOD has transformed the transportation system with services such as Uber, Lyft, etc. Individuals who rely on these types of services (i.e., carsharing and ridesharing) may also display an interest in using SAVs. These services are viewed as new technological advancements with the ability to impact the transportation system. They can be potential solutions to urban transportation such as reducing traffic and congestion, along with reducing the number of vehicles on the road (Greenblatt and Shaheen, 2015; Silberg, 2013). In this study, the latent explaining shared mobility will be modeled to analyze individuals' experience using MOD. Implementing MOD services as an indicator will give insight into the role it has in (S)AV acceptance. If consumers acknowledge the benefits from the use of these existing services, then it is highly predictable that there will be a high acceptance rate for the use of SAVs once available to the public.

H7: Latent shared mobility experience positively influences consumers' BI of AVs.

H8: Latent shared mobility experience positively influences consumers' BI of SAVs.

2.3.2 Green mobility experience

Although there are minimal studies that implement green lifestyle as a latent construct (e.g., Lavieri et al., 2017; Nair et al., 2018; Nazari et al., 2018), it has shown to have a major role in impacting (S)AV acceptance and it is hypothesized that green travel behavior can be a leading determinant in predicting SAV acceptance (Lavieri et al., 2017). Individuals with a green lifestyle have experience commuting through public transportation modes such as bus, train, subway, etc. The latent explaining green travel behavior analyzes individuals' green mobility patterns by measuring the type of public modes they use. The consideration of green lifestyle as a latent construct acknowledges all green travel behavior and potentially shows the relationship it has with influencing the use of SAVs.

H9: Latent green mobility experience positively influences consumers' BI of SAVs.

CHAPTER III

DATA

The proposed TAM is estimated using a sample dataset of the California Vehicle Survey conducted by California Energy Commission (2019) in the state of California. The sample dataset contains 3,723 individuals who are asked about their socio-demographic characteristics as well as their opinions about a number of attitudinal, perceptional, and preferential questions, which are discussed in sections 3.1 and 3.2, respectively.

3.1 Individuals' socio-demographic characteristics

Seven different socio-demographic attributes characterize respondents as shown in Table 2. The dataset categorizes individuals into two genders with nearly equal gender distributions between men and women at 53% and 47%, respectively. All respondents are 18 years of age and older, with individuals pertaining to one of the three generations: Millennials ($18 \leq$ age < 34), Generation X ($35 \leq$ age < 64), and Baby Boomers (age ≥ 65). Over half the respondents are Generation X with Baby Boomers trailing behind at 53% and 35%, respectively. Only a small minority of respondents identify as Millennials. Regarding employment, approximately half of the respondents are employed, with 40% unemployed, and 8% self-employed. Due to Baby Boomers accounting for one-third of the sample size, it is presumed they are among the unemployed individuals. There are three different income levels to which respondents pertain too, with half of the respondents earning around or above the median household income. The remaining sample size earns a low or high income, with a percentage of 21% and 27%, respectively. Respondents are further questioned in their education, selecting from four different options ranging from no college to a professional degree. Around two-thirds of the respondents graduated from college with an associate degree or higher, with only 8% having no college education. Overall, the majority of the respondents are well-educated individuals with at least some sort of college education. Regards to education, although most individuals have some experience in college, only a small significance are enrolled in college. Respondents are asked about their concurrent enrollment in college along with their student status, with about 4% of respondents enrolled in college, and 96% of adults not enrolled in school. Lastly, respondents answered the region in which they reside, selecting from the following: Los Angeles, San Francisco, San Diego, Sacramento, Central Valley, and the rest of California. Almost half of the respondents reside in Los Angeles, with the second most populated region being San Francisco, at 45% and 25% respectively. The rest are dispersed among the following regions, with less than 10% living in each of the remaining areas.

Table 2: Sample data for individuals' socio-demographic characteristics

Attribute	**Category**	**#observations**	**Share (%)**
Gender	Male	1962	53.30
	Female	1719	46.70
Generation	Millennials (18 ≤ age < 35)	428	11.50
	Generation X (35 ≤ age < 65)	1983	53.26
	Baby Boomers (age ≥ 65)	1312	35.24
Employment status	Employed	1957	52.57
	Unemployed	1467	39.40
	Self-employed	299	8.03
Income (annual)	Low income (income < $50K)	699	20.56
	Medium income ($50k ≤ income < $150K)	1782	52.43
	High income (income ≥ $150k)	918	27.01
Education	High school graduate or less	233	7.80
	Technical school or some college	568	19.02
	College graduate (A.S. or B.A.)	1127	37.73
	Post graduate work or degree	1059	35.45
Student	Full-time	49	1.32

	Part-time	43	1.15
	Online only	52	1.40
	Not enrolled	3579	96.13
Region	Los Angeles	1671	44.92
	San Francisco	882	23.71
	San Diego	352	9.46
	Sacramento	303	8.15
	Central Valley	220	5.91
	Rest of California	292	7.85

3.2 Individuals' opinions on attitudinal, perceptional, and preferential questions

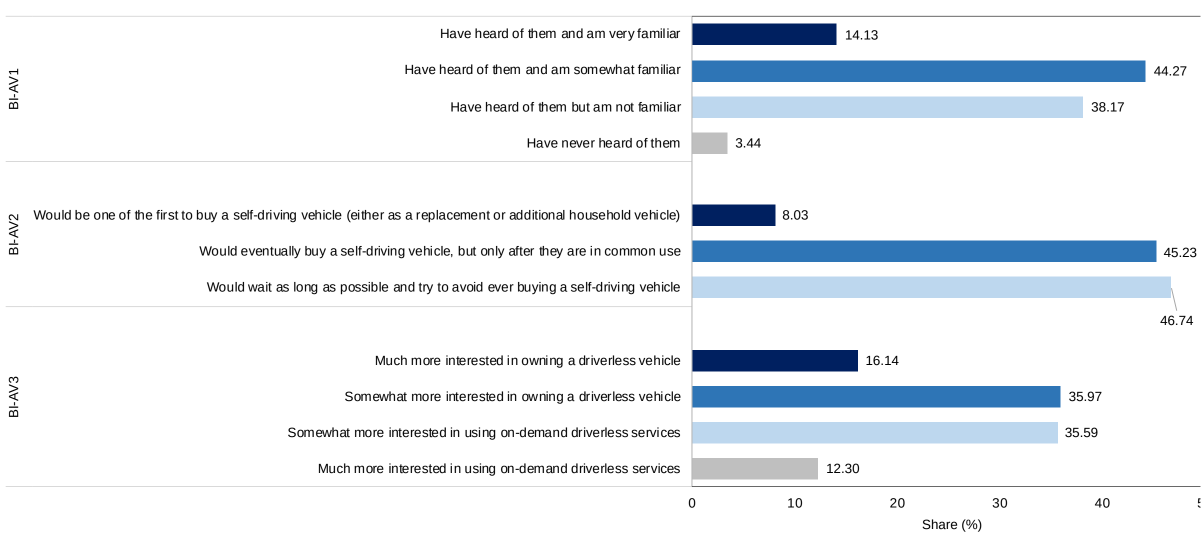
The measured indicators in TAM inquire information about consumer's interest in (S)AVs based on attitudinal, perceptional, and preferential questions to best forecast their intentions to purchase or own AV systems. The subsections in this section are structured in three parts based on Figure 1, providing statistical descriptions of individuals' responses to the corresponding indicators of each construct. In the first part, a series of questions ask respondents about their background and potential interest in using (S)AVs. These questions build the latent constructs forecasting BI-AV and BI-SAV. In the second part, respondents select their level of agreement using a four-point scale from "strongly disagree" to "strongly agree" based on questions regarding certain scenarios or opinions involving (S)AVs. Lastly, the survey collects information on respondents' attitudes with green and shared mobility in a four a four-point scale about their general experience with certain commutes in their residing area.

3.2.1 Behavioral intention to use AVs

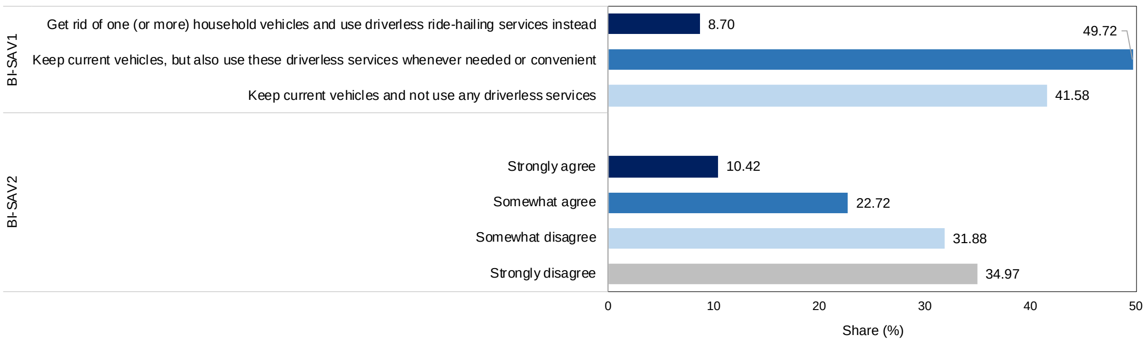
Figure 2(a) shows a statistical description of individuals' responses to latent construct BI-AV, which is built on three indicators, as shown below. Of the people surveyed, almost 60% have heard of autonomous or self-driving vehicles, responding "somewhat familiar" or "very familiar" with the concept. The remaining 40% have no familiarity with AVs. Furthermore, in response to the question about wanting to own AVs, respondents are almost equally dividend, with 53% expressing interest in eventually buying a self-driving vehicle and 47% preferring to "wait as long as possible and try to avoid ever buying." Similarly, in response to individuals' "relative interest in owning an AV versus using on-demand ride-hailing services," respondents are equally divided between both alternatives with owning or using, respectively at 52% and 48%.

3.2.2 Behavioral intention to use SAVs

The latent construct explaining BI-SAV is built on two measured indicators which question respondents' potential interest in "shared driverless services." As shown in Figure 2(b), in response to the question asking respondents how they would use "on-demand driverless ride-hailing services" if they were widely available, almost 50% responded with keeping their current vehicles but agreed to use driverless services when necessary. In contrast, approximately 42% of the respondents prefer to keep their current vehicles and avoid using driverless services. In addition, respondents were asked about the probability of using shared AVs with strangers if it meant a lower cost. Regardless of the cost, almost 67% somewhat or strongly disagree with the statement, with the remaining 33% agreeing to use shared services.



(a) Behavioral intention to use AV



(b) Behavioral intention to use SAV

Indicator	Definition of indicator
BI-AV1	Which of the following best describes your familiarity with 'autonomous' or 'self-driving' (i.e., driverless) vehicles?
BI-AV2	Consider your current situation with the vehicles your household now owns (if any), and imagine that driverless vehicles have become widely available for purchase. Which of the following scenarios best describes your household?
BI-AV3	Overall, what would be your relative interest in owning a driverless vehicle versus using on-demand ride-hailing services?
BI-SAV1	If on-demand driverless ride-hailing services were widely available today, which of the following best describes how your household would use these services and how it would impact the vehicle(s) you currently own?
BI-SAV2	I would be likely to use shared driverless services (even at lower cost) because I would want to share a vehicle with strangers.

Figure 2. Statistical distribution of behavioral intention to use (a) AVs and (b) SAVs (#obs = 3,723)

3.2.3 Perceived usefulness

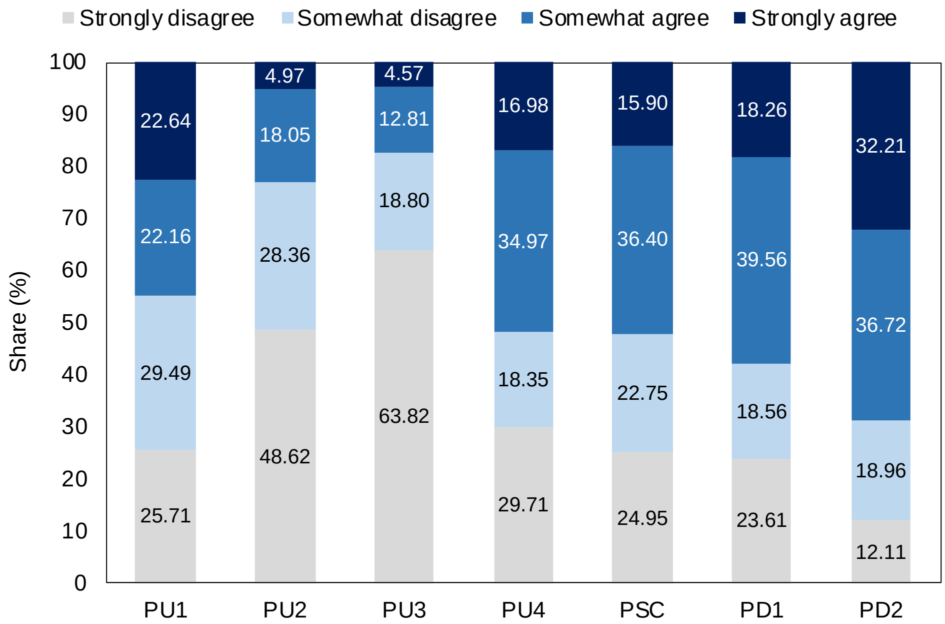
Figure 3 shows the statistical description of individuals' responses to the indicators of the latent constructs explaining perceptions of (S)AV features. In response to questions about the PU of (S)AVs, almost 55% of individuals state the unnecessity of having "self-driving vehicles." Furthermore, about 80% of respondents "strongly disagree" or "somewhat disagree" to reducing time at their workplace to "work more in the self-driving car." Respondents are further asked if they "would send an empty self-driving car to pick up/drop off" their child, and 83% neglected the opportunity if given with only 17% agreeing willingly. Although most individuals seem to disagree with the questions regarding PU of (S)AVs, almost 52% of respondents would use (S)AVs to travel when tired, sleepy, or under the influence of alcohol/medications.

3.2.4 Perceived safety concern

Regarding the statistical description of individuals' response to the indicators of perceived safety concern, there is only one question that builds the latent construct. About 52% of respondents would accept to ride a long time in a self-driving vehicle at a low speed to prevent dangerous scenarios from occurring to pedestrians and bicyclists. The remaining 48% "strongly disagree" or "somewhat disagree" with the statement.

3.2.5 Pro-drive attitude

In continuation with questions regarding perceptions of AV features, the latent pro-drive is built on two measured indicators. As shown below in Figure 3, 58% of respondents agree that riding a self-driving vehicle will allow them to enjoy traveling more, with 43% disagreeing with the statement. The second indicator asks individuals if they "would miss the joy of driving and being in control." Over half of respondents (69%) indicated that they "somewhat agree" or "strongly agree" with the statement, with 31% against it. Based on individuals' responses, the driver's enjoyment of driving may be a barrier hindering (S)AV acceptance.



Indicator	Definition of indicator
PU1	I see a need for self-driving vehicles.
PU2	I would reduce my time at the regular workplace and work more in the self-driving car.
PU3	I would send an empty self-driving car to pick up/drop off my child.
PU4	I would be able to travel more often even when I am tired, sleepy, or under the influence of alcohol/medications.
PSC1	I would accept longer travel times so the self-driving vehicle could drive at a speed low enough to prevent unsafe situations for pedestrians and bicyclists.
PD1	A self-driving vehicle would enable me to enjoy traveling more (e.g., watch scenery, rest).
PD2	I would miss the joy of driving and being in control.

Figure 3. Statistical distribution of perception of AV features (#obs = 3,723)

3.2.6 Shared mobility experience

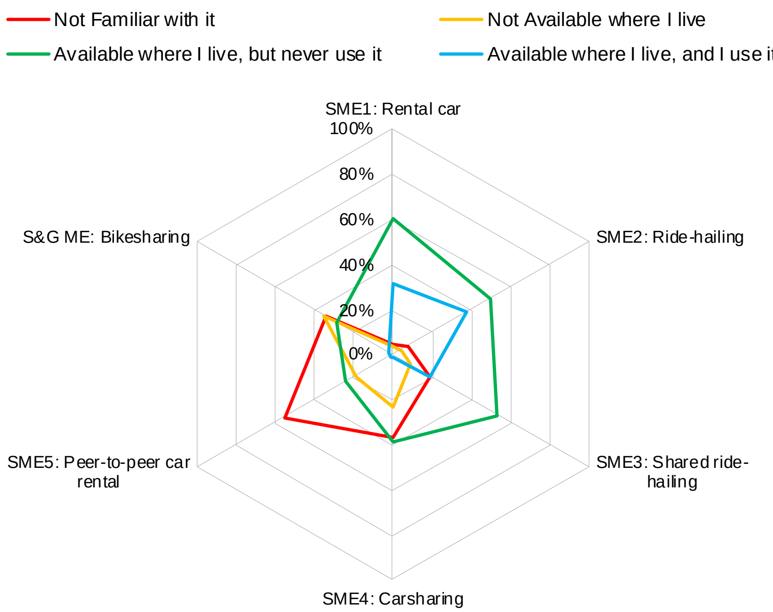
Figure 4(a) depicts a statistical description of individuals' responses to the six indicators corresponding to shared mobility explaining their experience and familiarity with certain modes. The set of questions assist in determining how many individuals use shared services, specifically to the following configurations: rental car, ride-hailing, shared ride-hailing, carsharing, peer-to-peer car rental, and bikesharing.

In general, respondents have greater access to the shared services unlike the availability of green travel. The most accessible shared MOD is ride-hailing, shared ride-hailing, rental cars, and carshare, however, approximately 60% of individuals do not use them. About 40% of the respondents take advantage of the MOD available in their areas, only using ride-hailing, shared ride-hailing, and rental cars. Further, based on Figure 4, a great portion of consumers are not familiar with peer-to-peer car rentals, carshare, bikesharing, and eBikes. Nevertheless, respondents' attitudes towards the indicators suggest only a small portion of individuals utilizing half the shared mobility offered in their areas. It may be that majority of respondents own and travel in a personal vehicle instead of using shared services considering that majority are either not familiar or reluctant with using shared AV systems.

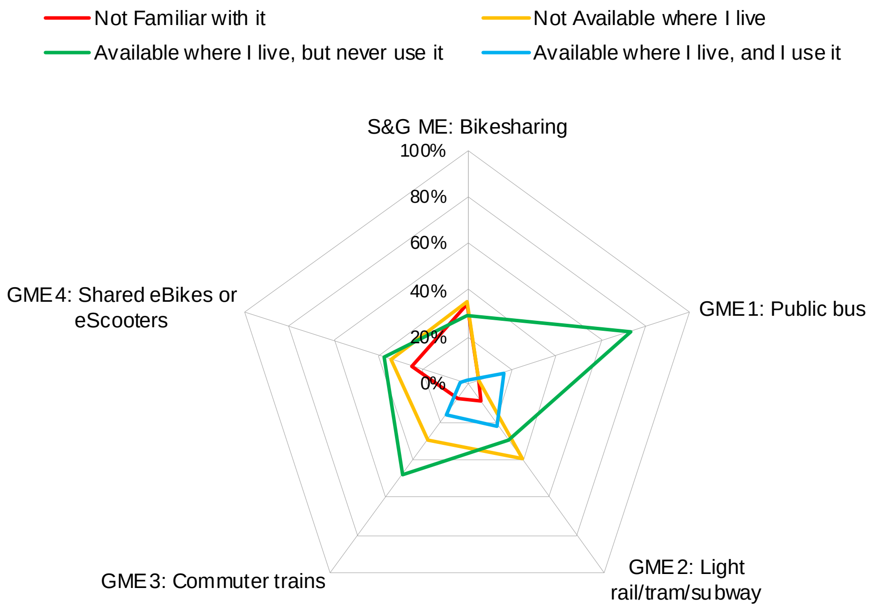
3.2.7 Green mobility experience

In continuation with travel behavior, the spider web in Figure 4(b) shows individuals' responses to the five indicators corresponding to the latent construct explaining their experience with green mobility. Transportation modes classified as green mobility are public bus, light rail/tram/subway, commuter train, shared eBikes or Scooters, and bikesharing.

The greatest response from the figure indicates that many individuals are acquainted with the different types of modes but have never used them. When interpreting individuals' green mobility patterns, around 80% of individuals are aware of the public bus, yet do not utilize it. Moreover, 60% of individuals have access to commuter trains and around 20-30% to eBikes/eScooters, bikesharing, and the light rail/tram/subway. Although the public has access to all the green commutes, consumers prefer other alternatives, with less than 20% of consumers actually using them (i.e., bus, train, and light rail/tram/subway). However, the difference when compared to shared mobility is the unavailability of certain commutes. About 40% of respondents do not have access to most of the modes except for the public bus as shown in Figure 4(b). What is noteworthy mentioning is that respondents have more familiarity with green mobility based on the percentage of respondents indicating it. Overall, the level of interest in green travel is relatively low, with respondents expressing a higher preference for using shared mobility.



(a) Experience with shared mobility



(b) Experience with green mobility

Indicator	Definition of indicator
	Experience with ... for trips in the local area
SME1	Rental car
SME2	Ride-hailing (Uber/Lyft)
SME3	Shared ride-hailing (UberPool/LyftLine)
SME4	Carsharing (Car2Go, ZipCar)
SME5	Peer-to-peer car rental (e.g., GetAround, Turo)
S&G ME	Bikesharing (e.g., Bay Area Bike Share)
GME1	Public bus
GME2	Light rail/tram/subway (e.g., BART, LA Metro)
GME3	Commuter train (e.g. Amtrak, Caltrain)
GME4	Shared eBikes or eScooters (e.g., Jump)

Figure 4. Statistical distribution of attitude towards (a) shared and (b) green mobility (#obs = 3,723)

CHAPTER IV

ESTIMATION RESULTS

The system of equations (shown in Figure 1) is coded using the software Statistical Analysis System (SAS) and estimated using structural equation modeling (SEM) technique. In this section, the estimated model is evaluated in chapter 4 and interpreted in sections 4.2 and 4.3.

4.1 Model evaluation

Table 3 presents the goodness-of-fit measures, usually reported by SEM studies, and the recommended measures (Kline, 2015). The measures are chi-square, goodness-of-fit index (GFI), adjusted GFI, Standardized root Mean Square Residual (SRMR), and Root Mean Square Error of Approximation (RMSEA) (Browne and Cudeck, 1992; Cheung and Rensvold, 2002; Kline, 2015; Schreiber et al., 2006).

Table 3: Goodness-of-fit measures

Goodness-of-fit measures	Estimated TAM	Recommended value
X^2/df	2.41	< 3.0
Goodness-of-fit index (GFI)	0.96	> 0.90
Adjusted GFI	0.94	> 0.90
Standardized root mean square residual (SRMR)	0.16	< 0.05
Root mean square error of approximation (RMSEA)	0.11	< 0.08

In reference to Kline (2015), the model chi-square ratio is significant with a p-value < 0.001. The chi-square ratio has limitations due to the probability of the fit hypothesis being implausible however, it is still widely observed in many SEM models (Kline, 2015). The GFI and adjusted GFI indicate the best fit when the threshold is higher than 0.9 (Cheung and Rensvold, 2002). The model's GFI and adjusted GFI meet the criteria with a value of 0.96 and 0.94. In continuation, the model surpasses the recommended value of SRMR < 0.08 and RMSEA < 0.06 (Schreiber et al., 2006), with a fit index of 0.16 and 0.11 for SRMR and RMSEA, respectively. The model's indices did not meet the two latter criteria, however, it is reasonable since it does not favor models evaluating large sample sizes, with recommendations of reporting the matrix of correlation (Kline, 2015).

4.2 Model interpretation: Using the estimation results

Figure 5 shows the estimation results of the measurement and structural equations connecting each latent construct to the underlying indicators via the estimated weights which are statistically significant at the level of 0.001. The structural equations represent the estimated coefficients with the latent constructs having a direct path to BI-AV and BI-SAV.

4.2.1 Estimated measurement equation model

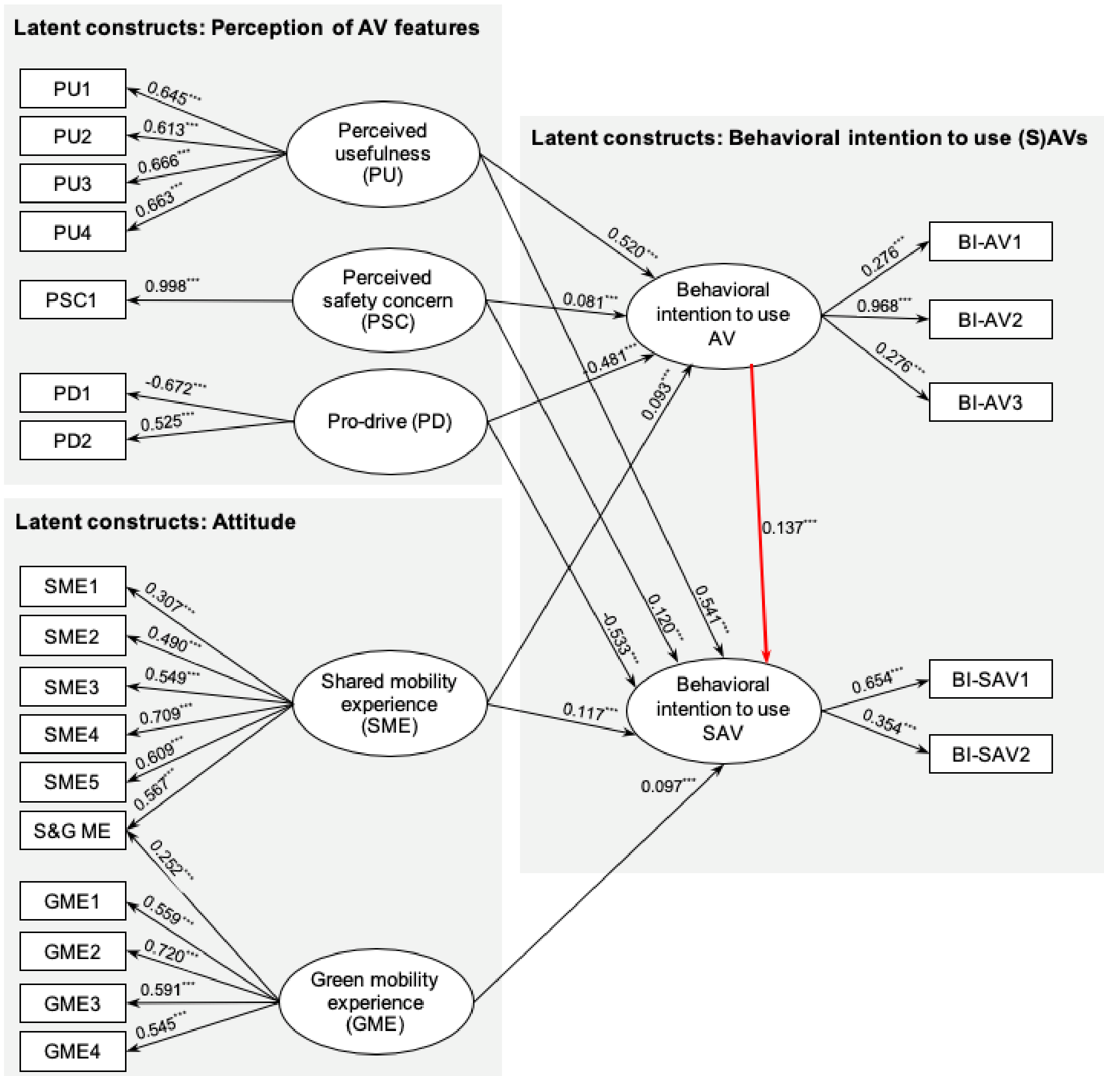
The measurement equations' substantial connections indicate if the indicators are significantly related to the latent construct they were supposed to measure. With a focus on Figure 5, latent variable BI-AV is built on 3 significant measured indicators, with the greatest effect from the indicator questioning respondents' intentions to purchase an AV. In response, individuals express potential interest in owning AVs, with some familiarity to their existence and capabilities. The latent variable predicting BI-SAV has positive loadings on all of its indicators. This clearly implies individuals' positive intent in using SAVs, especially with the latent greatest contribution based on the indicator related to respondents' decision of using SAVs when convenient.

All of the indicators in the latent construct explaining PU of (S)AVs have strong positive loadings, with similar estimated weights on all of them. This implies that individuals acknowledge the benefits and usefulness of embracing (S)AVs (Haboucha et al., 2017). Furthermore, the estimated weight of the measured indicator corresponding to perceived safety concern has the highest statistical significance from all latent constructs. This clearly implies that the indicator tied to the latent construct are highly associated with the responder's safety concerns, especially if individuals are willing to place their trust in an AV to create a safer environment for others. In contrast to the last two latent constructs, the latent explaining individual perceptions on pro-drive is the only variable to have a negative tendency from one of its corresponding indicators. However, this is reasonable since one of the indicators relates to individuals' enjoyment of driving. Individuals who enjoy driving are more likely to continue using their personal vehicle rather than expressing interest in autonomous services (Haboucha et al., 2017) which explains the negative sign.

Regarding travel behavior (i.e., shared, and green mobility), the latent construct explaining shared mobility experience has positive tendencies on the measured indicators corresponding to the publics' experience with using several commutes. The descending order of the highest estimated weights starts with carsharing, peer-to-peer car rental, bikesharing, shared ride-hailing, ride-hailing, and rental car. Finally, the latent green shared mobility also has positive loadings on all its indicators, in descending order of the highest estimated weights starting with light rail/tram/subway, commuter train, public bus, shared eBikes/eScooters, and lastly, bikesharing.

4.2.2 Estimated structural equation model

Figure 5 also shows the estimated coefficients of each latent variable in the SEM, revealing if the hypotheses made in chapter 2 are supported. Overall, the estimated results all have a positive effect on BI of AVs and SAVs, except for latent variable pro-drive, with PU having the strongest impact on user acceptance of (S)AVs. Similarly, existing studies found PU to be one of the main factors contributing to the propensity of AVs and SAVs (i.e., Hegner et al., 2019; Panagiotopoulos and Dimitrakopoulos, 2018), confirming H1 and H2 with estimated coefficients at 0.520 and 0.081, respectively. H3 and H4 were based on latent perceived safety concern positively affecting BI-AV and BI-SAV. The hypotheses are confirmed with estimated parameters at 0.081 and 0.12. Additionally, H5 and H6 are latent construct pro-drive negatively affecting BI-AV and BI-SAV, with both hypotheses supported with estimated coefficients of -0.481 and -0.533, respectively. This signifies pro-drive as a factor deteriorating (S)AV acceptance due to the negative sign. Moreover, the estimation results confirm H7 and H8 in terms of shared mobility positively influencing BI-AV and BI-SAV, with coefficients of 0.093 and 0.117. Green mobility is the only latent construct with one hypothesis (H9) towards BI-SAV due to insignificance towards BI-AV. H9 positively influences BI-SAV with an estimated coefficient of 0.097. Lastly, H10 states that BI-AV impacts BI-SAV, and the hypothesis is confirmed with a parameter of 0.137. It is assumed that individuals who accept AVs will lean towards user acceptance of SAVs as well. Overall, all the proposed relationships in the model are significant, confirming the hypotheses made based on the estimated parameters.



*****: significant at the confidence level of 0.001 level**

Figure 5. Estimation results of the proposed technology acceptance model

Spearman correlation is a statistical method used to measure the strength and association between variables. Table 4 shows the correlation between each latent variable since the model did not meet the SRMR and RMSEA criteria. Results show a strong and significant relationship with statistical significance at a level of 0.01. In addition, the matrix suggests all latent constructs have attained discriminant validity. This infers that the proposed model is a good depiction of the hypothesized relationships.

Furthermore, Table 4 presents PU as the strongest latent variable influencing BI, following with perceived safety concern. Pro-drive is the only factor negatively associated with BI-AV and BI-SAV. Regarding travel behavior, shared and green mobility also represent a positive correlation, however, green mobility is the weakest factor associated with BI-AV and BI-SAV. It is inferred those individuals with a green lifestyle will be the most reluctant towards using (S)AVs. Lastly, when comparing user acceptance between BI-AV and BI-SAV, the findings show the latent constructs have a higher correlation for SAV intent. This infers that the public will have a slightly greater interest and preference for the use of SAVs than AVs.

Table 4. Spearman correlation between the latent constructs

Latent constructs	Behavioral Intention to use AV	Behavioral Intention to use SAV	Perceived usefulness	Perceived safety concern	Pro-drive attribute	Shared Mobility Experience	Green Mobility Experience
Behavioral Intention to use AV	1.000						
Behavioral Intention to use SAV	0.961	1.000					
Perceived usefulness	0.891	0.900	1.000				
Perceived safety concern	0.625	0.658	0.527	1.000			
Pro-Drive	-0.880	-0.891	-0.701	-0.551	1.000		
Shared Mobility Experience	0.300	0.345	0.233	0.143	-0.156	1.000	
Green Mobility Experience	0.189	0.274	0.152	0.112	-0.124	0.556	1.000

Note: all correlation values are statistically significant at 0.01 level in Spearman.

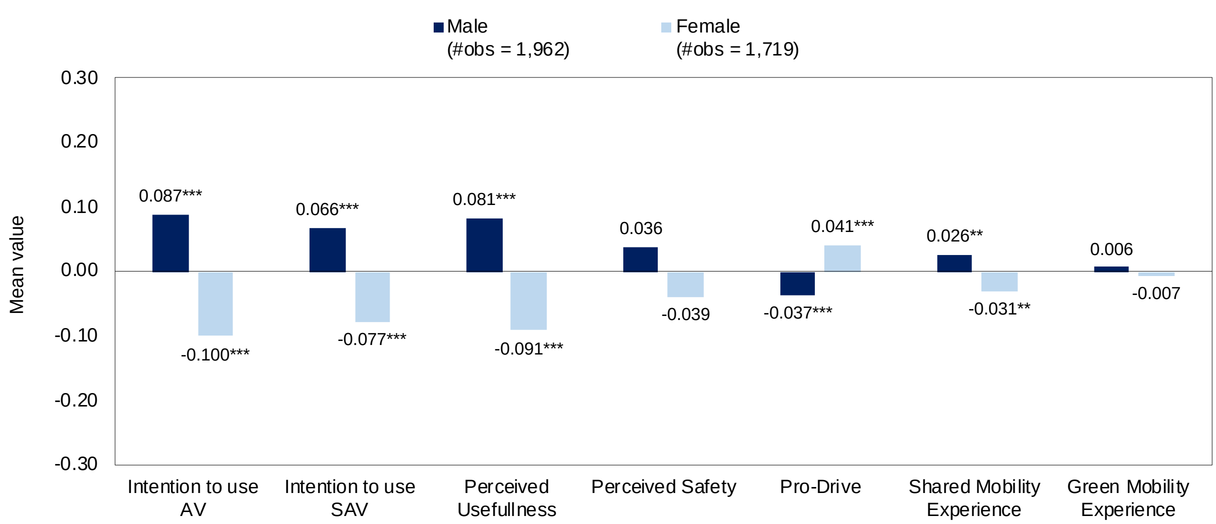
4.3 Model interpretation: Analyzing demographic heterogeneity across the latent constructs

The estimation results on the updated TAM signify how significant of an impact, if any, the latent variables have on predicting user intent of (S)AVs. The second statistical technique in this study is a post-estimation analysis of the explanatory variables. Post-estimation is a statistical technique of retrieving information from regression for further analysis, obtaining tables of estimated marginal means and a summary statistic of relevant data. The findings will be further evaluated by linking individuals' proclivities to each latent construct to their socio-economic variables to capture individuals' variation. Moreover, the social-economic characteristics that will be evaluated are gender, generations, employment, income, education, student classification, and region. Each socio-economic attribute will have its following subsection, with the post-estimation results shown in the figures below, with scrutiny on the mean values representing the significance level, if any, at the confidence level of 0.05, 0.01, or 0.001 on every latent construct. This method will be used to figure out what characteristics and aspects influence user acceptance of automated technologies.

4.3.1 Gender

Figure 6 shows the mean value across gender with 1962 males and 1719 females. Results found males highly inclined in using both AVs and SAVs, with a greater preference for AVs. A previous study by Becker and Axhausen (2017) did a literate review among acceptance of automated vehicles, and their results concluded that men, in general, are more optimistic about advanced driverless services. Lavieri et al. (2017) also concluded men are more likely to try carsharing services first as opposed to women. The only study to contradict this trend obtained empirical results based on a small survey of 32 individuals (Silberg, 2013). Females have a negative tendency towards all latent constructs, except for pro-drive, indicating their reluctance of accepting any automated technology. It seems that women consider greater aspects such as price, safety, risks, privacy, etc., and are more thoughtful before deciding on adopting (S)AVs (Dannemiller et al., 2021; Liljamo et al., 2018; Yuen et al., 2020). This concludes that gender is a socio-demographic variable that greatly affects BI of (S)AVs, since men are less concerned about the risks, with a previous study dictating that males express more trust and comfort in the presence of AVs (Paddeu et al., 2020).

In regard to the latent constructs affecting BI, males have a positive PU with great significance. In observing perceived safety concern, gender represents no significance, as mentioned previously, men are less risk concerned and open to the idea of new technology, and women do not acknowledge the advantages or importance of (S)AVs (Becker and Axhausen, 2017; Hulse et al., 2018; Kyriakidis et al., 2015; Sener et al., 2019). Latent construct pro-drive is significant in both genders, with females having a positive tendency towards the latent construct. Females would either miss the sensation of driving or have a preference towards having manual control of a vehicle. In continuation, there is a general preference for shared mobility, with a positive significance present only in males. Lastly, the latent construct explaining green travel behavior has insignificant mean values, with a greater preference in SAVs from males.



*** significant at the confidence level of 0.05; ** significant at the confidence level of 0.01; *** significant at the confidence level of 0.001**

Figure 6. The mean value of latent constructs across gender

4.3.2 Generations

Figure 7 represents the mean values for every latent construct across the generations. As categorized in Section 3.1, the sample size is composed of mostly Generation X ($35 \leq$ age ≤ 64) and Baby Boomers (age ≥ 65), with Millennials ($18 \leq$ age ≤ 34) having the least respondents. Based on the results in Figure 7, Millennials and Generation X are predicted to use (S)AVs, specifically AVs, based on the positive marginal effects from the latent constructs. The younger generations seem to appreciate the benefits from using advanced technologies, displaying an inclination towards the use of automated services. Existing studies have expressed young individuals to be the first respondents to possibly use AVs in the future, with older generations reciprocating negative perceptions, explaining the negative margins from Baby Boomers (Choi and Ji, 2015; Hardman et al., 2019; Liljamo et al., 2018; Sener et al., 2019; Zhang et al., 2019). Additionally, studies that focused solely on investigating SAV acceptance found younger individuals to have a greater interest in SAVs as well (Acheampong and Cugurullo, 2019; Haboucha et al., 2017; Lavieri et al., 2017; Nazari et al., 2018; Wang et al., 2020; Hardman et al., 2019). Similarly, the estimated results found in this study reveal younger individuals (i.e., Millennials and Generation X) inclined towards the use of (S)AVs.

In analyzing the latent constructs impacting BI, Baby Boomers are the only generation to have a negative perception of PU, with the remaining generations perceiving potential benefits from using them. Regarding perceived safety, Millennials are the only generational group to have a positive impact, meaning they perceive safety from using (S)AVs. On the other hand, Baby Boomers have positive mean values for latent construct pro-drive with a preference for traditional methods and reluctance towards giving up driving (Becker and Axhausen, 2017; Haboucha et al., 2017; Yuen et al., 2020). Generation X and Millennials express a negative effect on the latent construct, especially from the Millennials, as indicated by the negative mean value. Regarding shared and green mobility as shown below, Baby Boomers have a negative impact on travel behavior, suggesting that they travel in their own vehicles rather than use public transportations (Garikapati et al., 2016). Generation X is the only group to express significance in both travel modes, with the possibility of using both types of services, and Millennials, on the other hand, expressed no significance towards the use of green mobility, with a positive impact on shared mobility. Overall, there was a larger emphasis on shared mobility, with green travel patterns having the least impact across age lines.

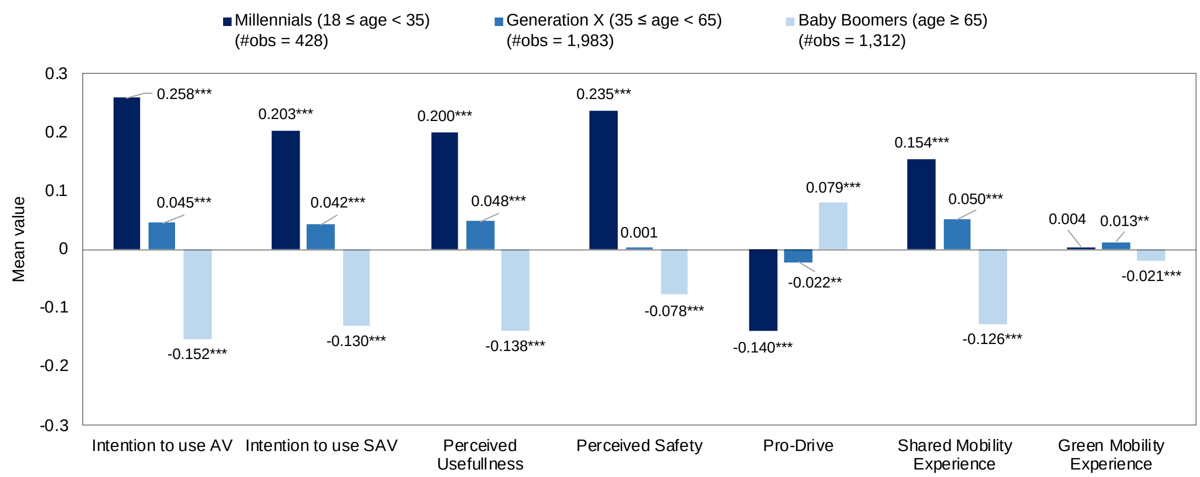


Figure 7. The mean value of latent constructs across generations

4.3.3 Employment status

Figure 8 provides the mean values for each latent construct across employment. Respondent's employment classification is categorized into three different categories: employed, unemployed, and self-employed. The respondents from the dataset are mostly employed or unemployed. This is understandable, considering that the second largest age group are Baby Boomers. The figure below shows employed and self-employed individuals having the greatest tendency towards user acceptance of (S)AVs, specifically employed individuals. Self-employed have a weak association with some of the latent constructs affecting BI, which in turn gives weaker effects towards BI. Lastly, retired individuals have no interest in owning or using (S)AVs, and as mentioned earlier, unemployed individuals seem to highly represent the Baby Boomers based on their reluctance in using (S)AVs. It can be concluded that employment is correlated to generations, with the unemployed not in favor of (S)AVs usage.

In analyzing the latent constructs related to perceptions of (S)AV features, unemployed individuals have a negative PU with similar results witnessed with perceived safety concern. Employed individuals are the only group to express positive significance for both constructs, yet with have negative mean values for latent pro-drive as seen below. Further, unemployed individuals are the only group to have a positive tendency towards the latent construct. Nazari et al. (2018) had analyzed employment and found retired individuals to have no interest in AVs with an interest towards them as an access/egress mode. Since employed individuals travel greatly for work purposes, they seem keen on expressing interest in (S)AVs due to possible accommodations and advantages once available for their personal use. Additionally, Morahan-Martin and Schumacher (2007) found workers more prone to being technological savvy, consistent with the ideology that individuals are exposed to more technology in the workplace. Latent constructs explaining travel behavior are only significant for the (un)employed. Employed individuals are the only category to have a positive tendency towards both travel patterns. There is a negative or neutral tendency from unemployed and self-employed individuals. There is a much greater significance for shared mobility compared to the factor scores of green travel patterns. Those who are employed seem to take greater advantage of the travel modes available in their areas to commute to work.

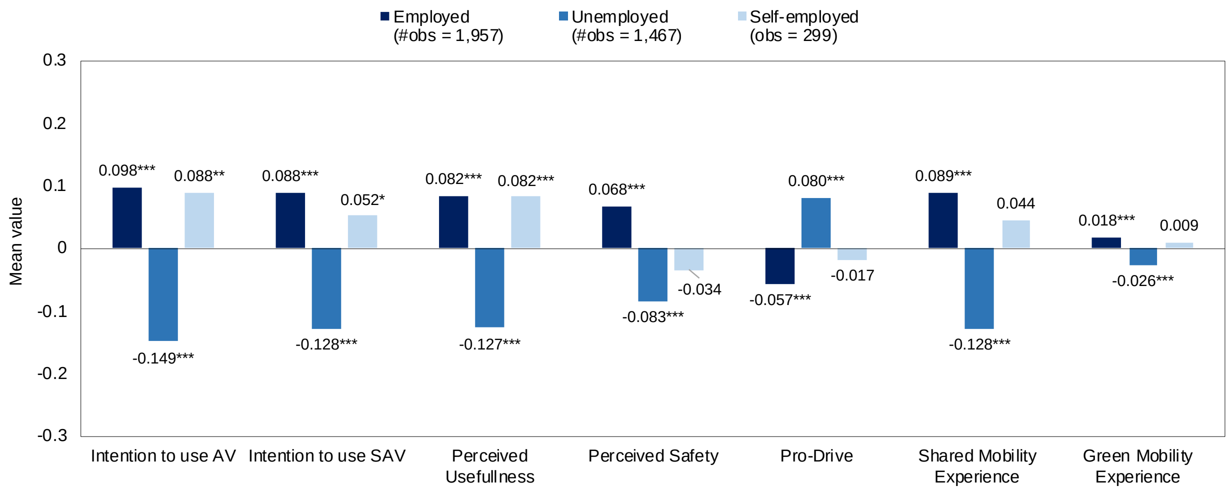


Figure 8. The mean value of latent constructs across employment status

4.3.4 Income

Overall, income proves to affect individuals’ response towards accepting and using (S)AVs as demonstrated in Figure 9. Income is categorized into three different groups: low, medium, and high (Table 2) and the mean values show that individuals with a high income are the only group to have positive tendencies towards BI of AVs and SAVs. Medium and low-income levels both expressed negative tendencies towards BI, with low-income being the least significant. According to Becker and Axhausen (2017) and Kyriakidis et al. (2015) people with higher earnings had the financial abilities to experiment with such vehicles first. However, those with less financial status did not have the same privilege to test and experience self-driving vehicles at early stages.

Individuals' proclivity for latent construct PU is depicted in Figure 9, with the strongest impact towards BI based on the significant confidence level. The remaining incomes have a negative tendency towards PU. Similarly with perceived safety, high income is the only category to have a positive association with the latent, with a negative or neutral significance from the remaining income levels. In continuation, pro-drive is significant in those with low- and medium-income, with negative significance from those with a high income. It is assumed that individuals with higher earnings have favorable views of automated vehicles having full control. The results reflect similarly with the socio-economic attribute of education, individuals who have no college degree express a positive tendency towards latent pro-drive, contradicting the results from those with higher education. In existing studies, education and income have a relation, implying that individuals with high education have a high income.

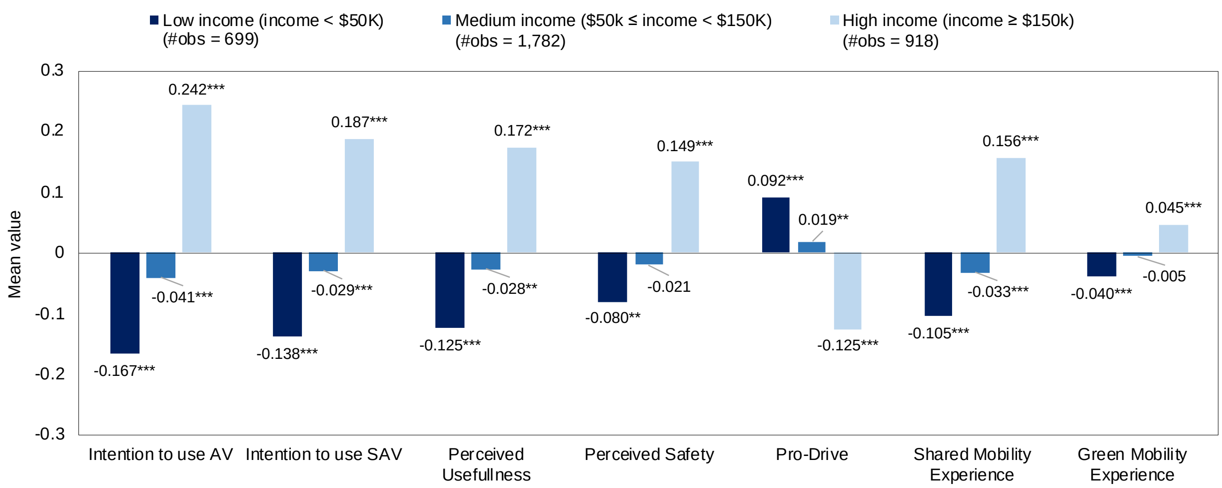


Figure 9. The mean value of latent constructs across income groups

Travel behavior in shared and green mobility is positively influenced by individuals with a high income, specifically in shared mobility. Those categorized with a low or medium income perceived a negative tendency towards all mobility patterns. Similarly, Lavieri et al. (2017) found individuals with higher incomes having a "larger carbon footprint," and those with lower incomes being less technological oriented with a negative perception towards (S)AVs. Their study had also mentioned that individuals with a low income were more associated with a green lifestyle; however, their results conflicted with the one from this study. Individuals with a low income reflect a negative tendency towards shared and green mobility as mentioned previously. It is assumed that those with low incomes have either no access to other transportation modes or commute in their own vehicle.

4.3.5 Educational attainment

Education is categorized into four different groups as noted in Figure 10, from high school education and ascending to post-graduate work. The figure shows the post-estimation analysis across education. Overall, education contributes a positive effect towards (S)AV adoption, specifically AVs, with positive tendencies from individuals with higher education. They seem to have a greater understanding and awareness of the influences and potential manifestation from owning or using such technology (Kyriakidis et al., 2015; Liljamo et al., 2018; Nair et al., 2018). On the contrary, individuals with no college degree have negative tendencies and show reluctance towards the idea of using any automated technology.

In analyzing the latent variables affecting BI, PU and perceived safety concern have similar results across the educational groups. Individuals with a higher education perceive (S)AVs as useful, foreseeing the benefits from adopting (S)AVs and having positive tendencies towards safety concerns. The remaining educational levels have a negative or neutral tendency towards the latent constructs. However, latent variable pro-drive reflects a positive significance in lower education levels. Individuals with lesser education have favorable views towards driving, and those with a high education perceive a negative significance on pro-drive. One may imply that individuals with higher education have a wider understanding or awareness of AVs and SAVs, the reason why they have a negative effect on the latent (Kyriakidis et al., 2015). Travel behavior seems to positively impact individuals with a college degree, resembling positive significance for shared and green mobility. Individuals without a degree have a negative tendency towards both latent constructs, assuming they rather transport in their vehicle than use alternative modes.

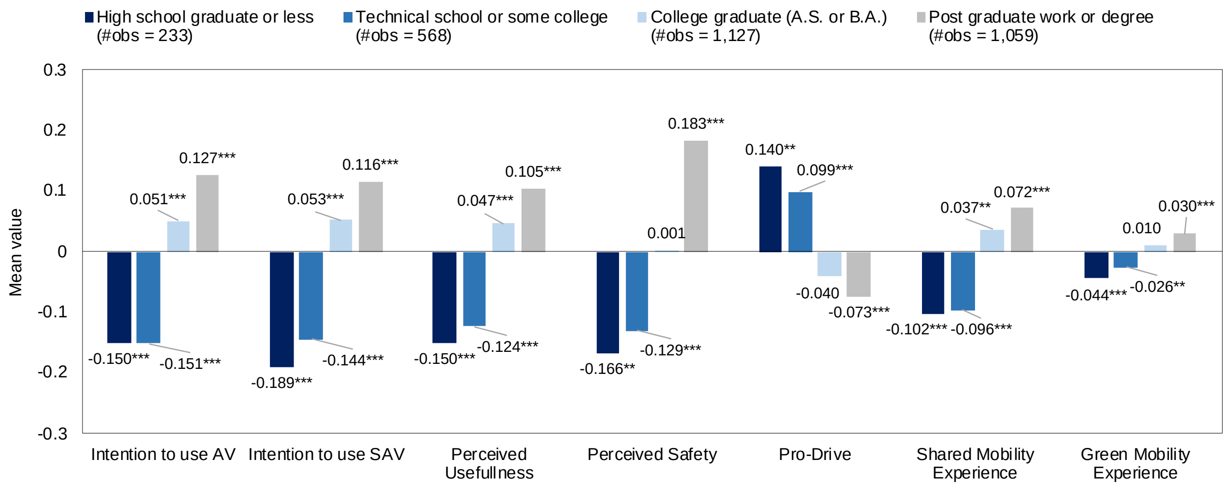


Figure 10. The mean value of latent constructs across educational attainments

Overall, the average value for shared mobility has a much greater significance over green travel behavior. This signifies those individuals with a college degree have a higher inclination for the use of shared MOD. Therefore, individuals with this preference are more likely to be acceptable of SAVs in the future based on the positive tendencies.

4.3.6 Student

Figure 11 details the mean values of the latent constructs across student status (i.e., full-time, part-time, online, and no school). In this study, the findings show that those enrolled in school have the greatest tendency on user acceptance of (S)AVs based on BI-AV and BI-SAV. With the exception of those not enrolled in school, there is a stronger proclivity towards the usage of AVs.

In analyzing the mean scores of the latent constructs, individuals enrolled full-time positively PU of (S)AVs, with the rest having negative or insignificant values. Regarding perceived safety concern, it is the latent variable with the highest significance from individuals' student status, except those not enrolled in school. Overall, results show that students tend to have a positive margin on PU and perceived safety concern, and this may be due to having a greater understanding or knowledge of technology, with some familiarity towards (S)AVs. In contrast to this, individuals' attitudes toward driving have negative or insignificant tendencies towards latent variable pro-drive. Further, the trend viewed in pro-drive is similar to PU, with no significance in any of the educational classifications except for part-time and online students. Haboucha et al. (2017) had argued that young individuals who had attended school with higher education were more likely to use AVs, with similar results reflected in this study. As mentioned previously, results showed that individuals with a higher education portray a positive tendency towards the use of (S)AVs and seem in favor of accepting self-driving vehicles. Additionally, individuals with an education are the most risk-seeking in the adoption of new technologies (Haboucha et al., 2017). Analyzing the results in travel behavior shows that full-time students are the only group to have a significant tendency towards latent construct explaining shared mobility experience. The remainder of the categories for both travel patterns have no significance. However, we still have to take into consideration that less than 4% of the respondents are students, so technically speaking, although there is a great interest in (S)AVs by students, the results are significantly low. Students probably express interest in MOD due to the flexibility and convenience of different modes available in transporting them to school. The results imply that education is a weak factor impacting the use of autonomous services, however, as mentioned previously, a very small percentage of respondents are students, so results are misleading. Further studies should investigate with a greater sample to fill in this gap, considering that relatively few studies observe a students' classification.

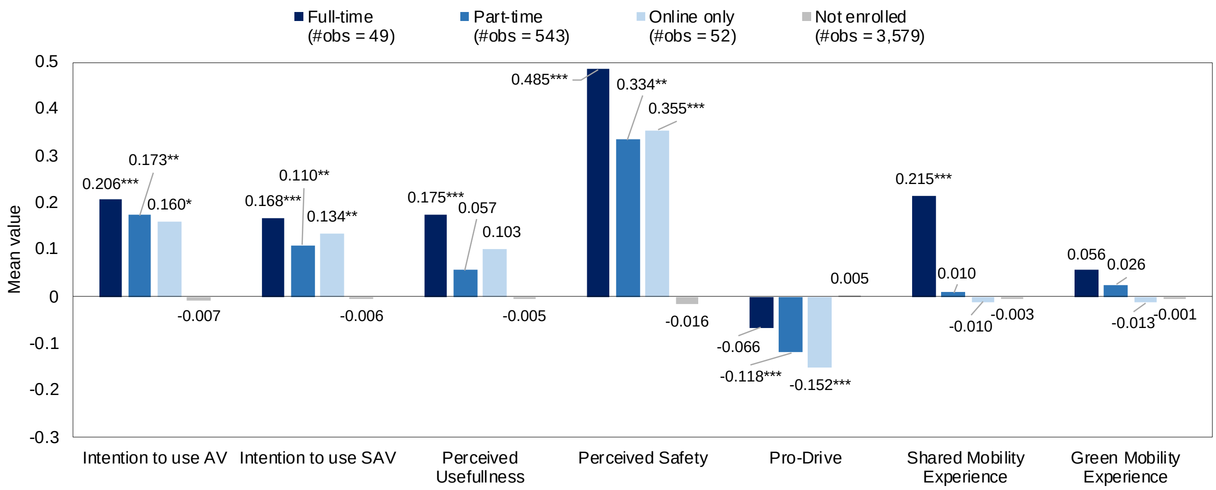


Figure 11. The mean value of latent constructs across student status

4.3.7 Region

Figure 12 presents the mean value of the latent constructs across the regions as followed: Los Angeles, San Francisco, San Diego, Sacramento, Central Valley, and the rest of California. Los Angeles and San Francisco are the most densely populated, with the other respondents residing in the remaining regions. Overall, in observing BI of AV and SAV, respondents residing in San Francisco are the only ones predicted to accept (S)AVs, with a higher preference for SAVs. The rest of the regions represent negative or insignificant values, including Los Angeles, considering that it is the most densely populated region. Moreover, San Francisco is the only region to express positive tendencies in majority of the latent constructs. This could be related to the fact that San Francisco is known for its advanced technologies and "smart city" installations (Lee et al., 2014), inferring that individuals residing in the area have an familiarity with autonomous technology and an understanding of (S)AVs potential benefits.

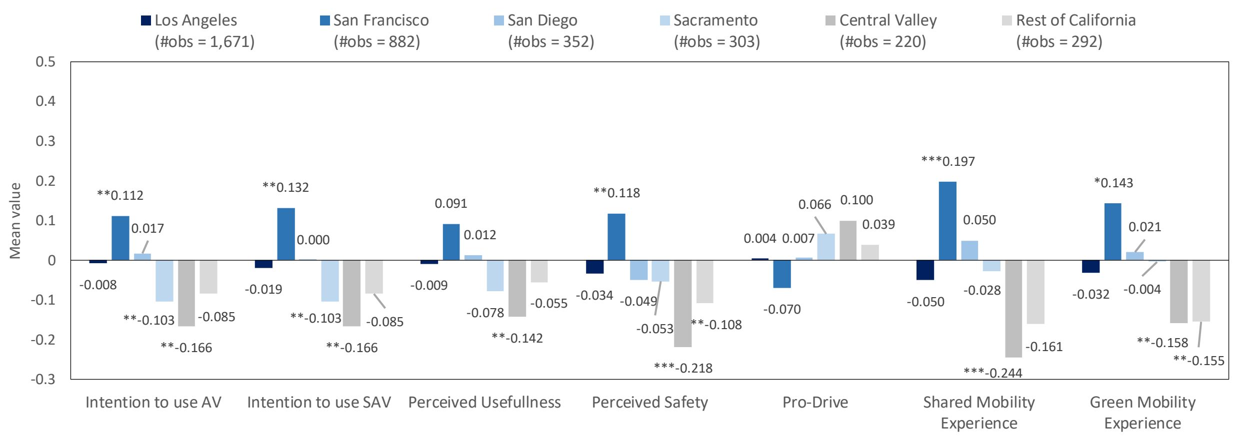


Figure 12. The mean value of latent constructs across regions in the State of California

In analyzing individuals' demographic heterogeneity across the latent constructs, San Francisco is the only region to positively influence PU, with the remaining regions having insignificant tendencies. Similarly, latent construct perceived safety concern only has a positive association with San Francisco. However, this is reasonable considering that it is the only region to have a negative impact on pro-drive. In continuation, out of the six regions, San Francisco, Sacramento, and Central Valley are the only regions to reflect any significance on latent construct pro-drive. Sacramento and Central Valley have a positive tendency, while San Francisco represents a negative one towards the latent. Regarding travel behavior, four regions portray significance towards shared and green mobility: Los Angeles, San Francisco, Central Valley, and the rest of California. Of the four regions, San Francisco is still the only region to have a positive association with travel behavior, with a higher significance in MOD. The remaining have negative or neutral associations with the latent constructs, with regions concluding as a weak attribute in impacting user acceptance of (S)AVs.

CHAPTER V

CONCLUDING REMARKS

(S)AVs are a new technological innovation with potential manifestations of impacting and transforming the transportation system. The accompanying benefits to the societies, such as safe, convenient, and efficient mobility, are dependent upon the public's acceptance and intentions to use (S)AVs. To recognize determinant factors of user acceptance of AV and SAV, this research proposes an updated technology acceptance model (TAM) contributing to AV acceptance literature in two ways. Firstly, this study is among the first attempts to focus on the behavioral analysis of individuals' SAV acceptance, where the existing studies mostly focus on AV acceptance behavior. Secondly, the proposed TAM encompasses two latent constructs explaining individuals' travel behavior, i.e., shared mobility experience and green travel pattern, which makes this study among the few ones considering these latent factors (Haboucha et al., 2017; Lavieri et al., 2017; Nair et al., 2018; Nazari et al., 2018).

To better understand consumers' level of interest in SAVs, incorporating travel behavior helped evaluate how individuals' mobility patterns influence the publics' future intended use of (S)AVs. Regardless of the majority of individuals owning and commuting in private vehicles, results indicate consumer's travel behavior to encourage interest in (S)AVs, specifically in SAVs with a greater percentage having accessibility and preference for shared MOD than green travel patterns. These latter constructs play a significant role in impacting user intent although they are the weakest contributions in TAM. While there is a significant association between shared mobility and BI, green mobility patterns only promote interest in SAVs. It is noteworthy mentioning that the respondents from the survey have a minimum association with green mobility patterns, which may play a factor in this.

In addition, PU, pro-drive, and perceived safety concern confirm the suggested hypotheses and also contribute to predicting consumers' acceptance of (S)AVs. PU is the strongest predictor in positively impacting user intent for both AVs and SAVs, which implies that consumer's main importance when considering utilizing (S)AVs is how valuable and useful they believe it will be in contrast to alternative commutes. The latent construct explaining perceived safety concerns has a significant impact in predicting BI although it is not the strongest factor. Regardless, it supported the hypotheses made for both AVs and SAVs, with individuals willing to place their trust in self-driving vehicles to create a safer environment for others (Xu et al., 2018). However, driver's enjoyment in driving hinders acceptance towards automated technology with negative marginal effects in acceptance for both AV systems, as found in two existing studies (Haboucha et al., 2017; Hegner et al., 2019). Findings from the model do conclude consumers having greater interest and propensity in SAV acceptance over AVs. Fagnant and Kockelman (2015) mentioned that SAVs would eventually replace conventional vehicles with greater benefits compared to owning an AV. Additionally, Zmud et al. (2016) stated that the public would prefer using SAVs rather than owning an AV to first experiment with a self-driving vehicle. In conclusion, all latent constructs play a major role in consumers' BI for (S)AV acceptance, with the model explaining AV and SAV acceptance at 51.70% and 78.68%, respectively.

Moreover, this study analyzes heterogeneity across different socio-economic characteristics, with respondents' tendencies measured to each latent variable. Age is interpreted in generations to target a larger representative sample. Millennials are predicted to be the first group in adopting self-driving vehicles, with greater interest in SAVs. Baby Boomers are reluctant in owning or using (S)AVs, with no interest in automated technology, as witnessed in an existing literature review (Gkartzonikas and Gkritza, 2019b). Gender plays a significant role, with men likely of using (S)AVs in contrast to women. AV studies evaluating income showed no effect on behavioral intent (Lee et al., 2019; Panagiotopoulos and Dimitrakopoulos, 2018; Sener et al., 2019), yet it contradicted studies investigating SAV acceptance (Haboucha et al., 2017; Wang et al., 2020). This study found income and education a significant role in effecting (S)AV acceptance. Individuals with high education and income are more inclined in (S)AV usage, although a few studies did not find education to be significant (Hegner et al., 2019; Lee et al., 2019; Zhang et al., 2019). Student classification has an insignificant effect considering a very small percentage of respondents are classified as students. Regarding employment status, employed individuals have an interest in using (S)AVs, with the unemployed negatively affecting (S)AV acceptance. As mentioned previously, the unemployed probably represent the Baby Boomers, who have negative tendencies towards (S)AVs. Lastly, not all regions impacted BI, with the greatest contribution coming from one of the most populated regions, San Francisco. This study has been, thus far, the second one to analyze regions as a socio-economic attribute to predict BI of (S)AVs (Wang et al., 2020).

5.1 Policy implications

The unobservable factors in the estimated model have great significance in the propensity of (S)AVs, and the results provide policymakers with three important insights into preparing for an upcoming era of (S)AVs.

The manifestation of (S)AVs promises benefits to society, including the ability to provide a new method of mobility for older individuals unfit for driving. However, based on the results obtained in section 4.3, Baby Boomers (i.e., older drivers) are reluctant in accepting the usage of (S)AVs. Our findings suggest that as (S)AVs become more accessible, young drivers will be the first to reap their benefits. While this is a positive outcome, previous studies emphasize older drivers could enhance greater benefits from the acceptance of (S)AVs due to limitations related to their age and their disabilities forbidding them to drive (Levitas et al., 2007; Li et al., 2019). As witnessed in existing studies, older drivers are the primary group of drivers rejecting the idea of adopting AV systems (Choi and Ji, 2015; Hohenberger et al., 2016; Levitas et al., 2007; Liljamo et al., 2018; Panagiotopoulos and Dimitrakopoulos, 2018; Sener et al., 2019) and appropriate actions should be taken to increase older drivers acceptance rate. Policymakers and planners should advertise and promote the potential benefits that may benefit Baby Boomers to increase awareness and marginal effects in future reference when investigating (S)AV acceptance.

Analyzing perceived safety concern gave insight into understanding that safety is a dominant factor impacting (S)AV acceptance (Dannemiller et al., 2021). Individuals who are older, have low income, women, unemployed, and with a low educational status have negative concerns about (S)AVs promise of delivering safety. In response to this, policymakers should provide information to address the issues and concerns the public may have regarding AV-related safety concerns. By addressing the safety concerns some of these individuals have, not only does it increase safety in AV systems, but it promotes reliability for accepting self-driving vehicles.

Lastly, it is worth highlighting that travel mobility made the least impact when exploring (S)AV acceptance due to few individuals commuting through public transport. According to policymakers, there should be a greater emphasis for (S)AV development to be steered in a direction that will complement public transportation (Fraedrich et al., 2019). Leading AV systems in this direction will create a sustainable environment and recommend (S)AVs as a method to not only promote the use of public transport but lead it in a direction of shared mobility.

5.2 Study limitations and future research directions

Results in this study are significant, providing greater depths to existing gaps, however, with some limitations for further research. Travel behavior, i.e., shared and green mobility should have impacted both AV systems, considering that Lavieri et al. (2017) found a positive association with the same two constructs affecting BI in both AV systems. Data used for the empirical study shows respondents having little interaction with green mobility, which may play a part in why it did not affect AV acceptance. Additionally, the survey's respondents have a minimum association with alternate modes of transportation; if individuals have higher association with MOD and green mobility, perhaps the latent constructs could have had a much greater influence and produced different findings. Second, this model proposed a TAM without incorporating perceived ease of use, it may be worthwhile exploring how the latent construct could have impacted the findings in this study if kept in the model. Lastly, while the representative sample is generalizable, it is noteworthy to mention that the database is from the state of California. California is one of the few existing states authorizing legal use of AVs (Lee and Hess, 2020). The respondents may have a greater familiarity with (S)AVs in contrast to other states with different legal, political, or technological aspects which may affect the results in this study, in contrast to other regions with less familiarity of self-driving vehicles.

While travel behavior research on (S)AVs is still in its early stages, several options for future research remain open. First, future research efforts should focus on addressing the data limitations present in this study. Second, there should be a greater emphasis on AV papers exploring SAV acceptance considering the limited number of existing studies and the public's greater interest in shared AVs. It is more realistic to investigate the publics' behavior intent to use SAVs if considering their mobility patterns with Becker and Axhausen (2017) stating the importance of modeling travel behavior due to positive significance in existing studies. Lastly, Xu et al. (2018) performed an experimental study analyzing individuals' perceptions before and after riding in an AV. Their results were significant and showed individuals had greater interest in adopting after experiencing an AV. Their study emphasized that the best way to predict actual usage is by having individuals experience AVs firsthand instead of relying on online surveys due to possibly reducing the validity of findings.

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BIOGRAPHICAL SKETCH

Yellitza Soto graduated from the University of Texas at Rio Grande Valley with a B.S Civil Engineering degree in May of 2019 and earned a Master of Science in Civil Engineering in August of 2021. Her concentration was transportation and worked on her thesis with support and guidance from her advisor Dr. Fatemeh Nazari. Her thesis investigated humans' behavioral intentions towards accepting and using both private and shared automated vehicles by proposing a psychological model.

She has attained past experience in a summer internship with Texas Department of Transportation, where she worked under a PE in transportation, giving duties and responsibilities of overseeing the rehabilitation of a roadway. Her contact email is Soto.Yellitza10@gmail.com.