# What Drives the Use of Shared Autonomous Vehicles: Empirical Evidence from California

Md. Mokhlesur Rahman[1,2] and Jean-Claude Thill[3]

[1]Assistant Professor, Department of Urban and Regional Planning, Khulna University of Engineering & Technology, Khulna-9203, Bangladesh &

[2]Postdoctoral Research Scholar, The School of Information Studies, 343 Hinds Hall, Syracuse University, Syracuse, NY 13244, United States. Email: mrahman.buet03@gmail.com, mrahma18@syr.edu

[3]Distinguished Professor, Department of Geography and Earth Sciences & School of Data Science, University of North Carolina at Charlotte, 9201 University City Blvd, NC 28223, USA

Abstract

The study investigates people's perceptions of Shared Autonomous Vehicles (SAVs) and the key determinants of household intentions to use SAVs using a structural equation modeling framework. Data were sourced from the 2019 California Vehicle survey to estimate the complex association between dependent and independent variables via mediators. Results indicate that higher educational attainment, income, labor force participation, Asian population origin, and urban living are negatively associated with SAVs. In contrast, young and working-age adults are positively associated with SAVs. Study results also show that people who prefer public transportation, car-sharing, ride-hailing, and ride-sharing services are more likely to use SAVs. The perceived usefulness, enjoyment, safety associated with Autonomous Vehicles (AVs) and prior knowledge of AVs significantly influence people to use SAVs, while the enjoyment of driving and the fear of losing control of vehicles are dissuasive factors. The study concludes that people's travel behaviors, positive attitude to shared mobility, and psychological features of AVs are the key determinants of SAVs.

Keywords: Shared Autonomous Vehicle, Public Acceptance, Theory of Planned Behavior, Theory of Reasoned Action, Technology Acceptance Model, Structural Equation Modelling

## 1. Introduction

The emergence of smartphones and the social, economic, and environmental impacts of automobiles motivate people to use shared mobility options. New shared mobility options, such as car-sharing, ride-sourcing, and certain micro-mobility services, allow people to rent vehicles for the short-term and enjoy mobility as a service (Hu & Creutzig, 2022; Machado et al., 2018). It has been argued that shared mobility would efficiently manage people's travel demand by increasing the occupancy of vehicles and thereby reduce traffic congestion, energy use, and emissions (Chan & Shaheen, 2012; Hu & Creutzig, 2022). The usefulness of shared mobility can be further enhanced by integrating Autonomous Vehicles (AV) technologies and developing Shared AVs (SAVs) services. This new business model would provide low-cost driverless and on-demand mobility services, increase vehicle efficiency, reduce congestion and emissions, facilitate multimodality, and ensure clean and sustainable transportation (Fagnant & Kockelman, 2018; Golbabaei et al., 2021).

SAVs can be seen as disruptive as they may transform people's lifestyle and travel patterns, transportation systems, and natural and built environments. Given the evolving socio-technical system of SAVs, how people would respond remains unsettled, while transport professionals and local public authorities are working at scoping adjustments to regulatory frameworks and infrastructures for SAVs (McKenzie, 2020). To the best of our knowledge, only a few studies have investigated public attitudes towards SAVs and the factors that may lead people to use SAVs. These studies tend to fall short, however, owing to a variety of reasons, including their use of hypothetical stated choice experiments and low sample sizes (Krueger et al., 2016). Nonetheless, people's willingness to accept this new technology is key to higher use of SAVs and to having them realize their potential benefits (Mara & Meyer, 2022; Paddeu et al., 2020). Realizing the importance of public perceptions and advancing the extant literature, this study investigates the key determinants of people's Behavioral Intentions (BI) to use SAVs for daily travel purposes. To this end, the following research questions are used:

1) How would people's socioeconomic and demographic characteristics influence them to use SAVs for their travel purposes?
2) How would awareness, perceived convenience, comfort, and safety influence the tendency of people to use SAVs?
3) How would factors of the built environment, transportation, and technology influence people to use SAVs for meeting their travel demands?

The rest of the paper is organized as follows: Section Two summarizes the relevant literature, introduces research hypotheses, and explains the theoretical framework of the study. The research design is outlined in Section Three. The main results of the study are reported in Section Four. Section Five articulates the discussion of these empirical results. Conclusions are drawn in Section Six.

## 2. Literature review and theoretical framework

### 2.1 Findings from past studies

SAVs are the convergence of shared mobility, AV technologies, smartphone services, and electrification; they are considered one of the most disruptive innovations of modern technological advances (Golbabaei et al., 2021; Stocker & Shaheen, 2018). SAVs can be shared exclusively by a travel party or simultaneously by multiple travel parties (Paddeu et al., 2020). Although shared mobility has been extensively studied, understanding the characteristics of potential SAV users and identifying the potential opportunities and challenges of SAV adoption have drawn attention recently only. These studies have mainly investigated consumer preferences for SAVs, operational mechanisms, and the effect of SAVs on vehicle ownership and last-mile travel (Maeng & Cho, 2022; Menon et al., 2018; Moorthy et al., 2017).

Extant research has found that male, young and working-age individuals, students and part-time workers, higher educational attainment, and black individuals are positively disposed towards SAVs (Barbour et al., 2019; Cartenì, 2020; Zhou et al., 2020). In contrast, the elderly, people with high income, households with children and a higher number of workers, single individuals, and full-time employees would be less likely to use SAVs (Hao et al., 2019; Krueger et al., 2016; Lavieri & Bhat, 2019). Although high income people and single individuals are unwilling to use SAVs, they are more inclined to use private SAVs (Gurumurthy & Kockelman, 2020; Lavieri & Bhat, 2019; Wang et al., 2020). Additionally, the elderly who aspire to engage in more social activities and have limited capability to travel are more interested to use SAVs (Hao et al., 2019). Thus, travelers' socioeconomic and demographic factors significantly influence their behavioral intentions to use SAV for travel purposes.

Researchers have found that individuals with inclination towards transit and multimodal travel, and with carsharing tendencies, those traveling by car as a passenger, and without a driver's license are more likely to use SAVs due to their pro-environment quality, their innovation content, convenience, and scopes for social interactions (Asgari et al., 2018; Lavieri & Bhat, 2019; Zhou et al., 2020). In contrast, the tendency to travel alone and higher vehicle ownership are negatively associated with SAVs (Hao et al., 2019; Lavieri et al., 2017). Previous studies also found that people are more likely to use SAVs for long distance business trips (Gurumurthy & Kockelman, 2020) and less likely to use them for recreational/leisure trips (Lavieri & Bhat, 2019). Therefore, people's previous and current travel behaviors could describe their intentions to use SAVs.

Breach of privacy, personal safety concerns, legal issues, insurance liabilities, and additional travel time for servicing other passengers could be major barriers to use SAVs (Asgari et al., 2018; Cartenì, 2020; Merfeld et al., 2019). Despite open-minded attitudes to accept AVs, many people are still reluctant to use AVs without a driver or share AVs with strangers (Wang et al., 2020). However, productive use of travel time and prior criminal background check could overcome this barrier. Researchers also found that perceived performance (i.e., the capacity of services, on time service, time saving, low congestion and emission), perceived ease of use, compatibility with novel technology, cost-effectiveness, hedonic motivation (i.e., fun, enjoyable, and pleasant), perceived norm (i.e., the influence of friends, availability on roads), and perceived behavioral control (i.e., knowledge, skill, time, money, preference) positively influence people's behavioral intentions to use SAVs (Hao et al., 2019; Merfeld et al., 2019; Wang et al., 2020). Tech-savviness, prior knowledge and use of advanced technology (e.g., automated braking, lane and parking assistance), higher level of vehicle autonomy, enabling mobility for physically impaired individuals, and appropriate legal clarity (i.e., accident liability lies with service providers) could increase people's tendency to use SAVs (Cartenì, 2020; Lavieri et al., 2017; Maeng & Cho, 2022). Additionally, prior involvement in traffic crashes increases people's willingness to use SAVs (Barbour et al., 2019). So, psychological factors have major roles to motivate people to use SAVs. However, researchers also reported that people who use SAVs are less concerned about safety, security, privacy, reliability, travel time, and costs (Barbour et al., 2019).

Research has found that social acceptability is the key to increasing SAV use (Paddeu et al., 2020). In this respect, critical components include improved mobility, accessibility and safety, reduction in environmental impacts, and ensuring social equity with regards to race, ethnicity, age, and disability status. Thus, given that the public rollout of SAV services are still in the design and planning stage, they may be well positioned to overcome the deficiencies of other travel modes.

People who live in urban areas are more likely to use SAVs compared to people who live in rural and less urban settings (Lavieri & Bhat, 2019; Merfeld et al., 2019). Researchers have also mentioned that demand for SAVs would be higher in megacities where facilities for vehicle parking are limited (Merfeld et al., 2019). Thus, considering the context of urbanization, privately owned AVs are more feasible in rural or suburban areas and SAVs are practical in urban areas (Merfeld et al., 2019). Although Wang et al. (2020) observed no significant impact of geographic location, they indicated that the availability of parking space at home or near residence significantly influences the propensity to share or own an AV. Barbour et al. (2019) noticed higher use of SAVs among the individuals who live close to grocery stores. Etminani-Ghasrodashti et al. (2021) explained that a supportive built environment (i.e., access to sidewalks, ramps, and curb cuts in pick-up and drop-off points) increases SAV use by the people with disabilities. The extant literature explains that, besides socioeconomic, transportation, psychological and social aspects, the factors of the built environment have a significant role to determine people's BI to use SAVs.

## 2.2 Theoretical framework

Adjei and Behrens (2012) have categorized the existing theories of human behavior for choosing among discrete alternatives based on the following questions:

- How choices are made from different alternatives (e.g., rational choice theory)?
- What factors affect the choice for an alternative (e.g., theory of planned behavior)?
- When does behavior change occur (e.g., cognitive theory)? and
- How do decision makers respond to behavioral change interventions (e.g., self-perception theory)?

These theories explain that people's behaviors respond to both internal factors --such as attitudes and norms-- and other external factors --such as incentives, institutional constraints (Adjei & Behrens, 2012). Among them, the Theory of Reasoned Action (TRA) is widely recognized in social psychology to explore the core determinants of people's BI towards an action (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1977; Madden et al., 1992). The central concept of the TRA is that people's BI for a specific action is jointly determined by individual's positive or negative attitudes and by subjective norms that indicate the influence of other people on behavioral action.

Some studies have used the Theory of Planned Behavior (TPB) to investigate the psychological factors that influence people's travel mode choices (Bamberg, 2006; Bamberg et al., 2003; Heath & Gifford, 2002). However, the surrounding built environment also influences travel behaviors. Consequently, Ajzen (1985) first introduced the TPB theory based on TRA to investigate the influence of external factors on behavioral actions. The TPB explains that human behavior depends on the person's intention to take some action (Morris et al., 2012; The World Bank, 2007). Their intentions are influenced by attitudes, subjective norms, and perceived behavioral control measures (i.e., ability, opportunity, resources, skill).

The Technology Acceptance Model (TAM) is a widely used framework to understand how users accept and use a technology (Lee et al., 2003; Zhang et al., 2020). Davis (1985) initially proposed the TAM based on the TRA (Fisbein & Ajzen, 1975). According to the early TAM, users' attitude is the main factors to understand people's BI to accept or reject. However, Perceived Usefulness (PU) and Perceived Ease of Use (PEU) define user's Attitude Towards Technology (ATT) (Davis, 1985; Davis et al., 1989). ATT denotes the positive or negative feelings about the performance of a technology. PU is defined as the degree to which a technology can enhance the job performance of the users. In contrast, PEU is defined as the degree to which it can reduce overall, physical and mental effort of the users. The model also demonstrates that the external features indirectly influence the attitude and beliefs of the users by directly affecting PU and PEU. Although, the earlier version of TAM indicates that ATT is the main factor (Scherer et al., 2019), Davis (1989) argued that ATT is not an influencing factor, but rather PU and PEU have direct and positive effects on the intentions of individuals toward technology use (Rahman et al., 2017).

2.2.4 Theoretical framework of the BI to use SAVs

Based on the extant literature and core concepts of behavioral theories, a theoretical framework – Integrated Technology Acceptance Model (ITAM) – is developed to investigate the factors of people’s BI to use SAVs. The proposed ITAM (Figure 1) features the behavioral control factors, objective factors, and people’s attitudes towards AVs that influence the SAV use intention. It is aligned with the updated TAM.

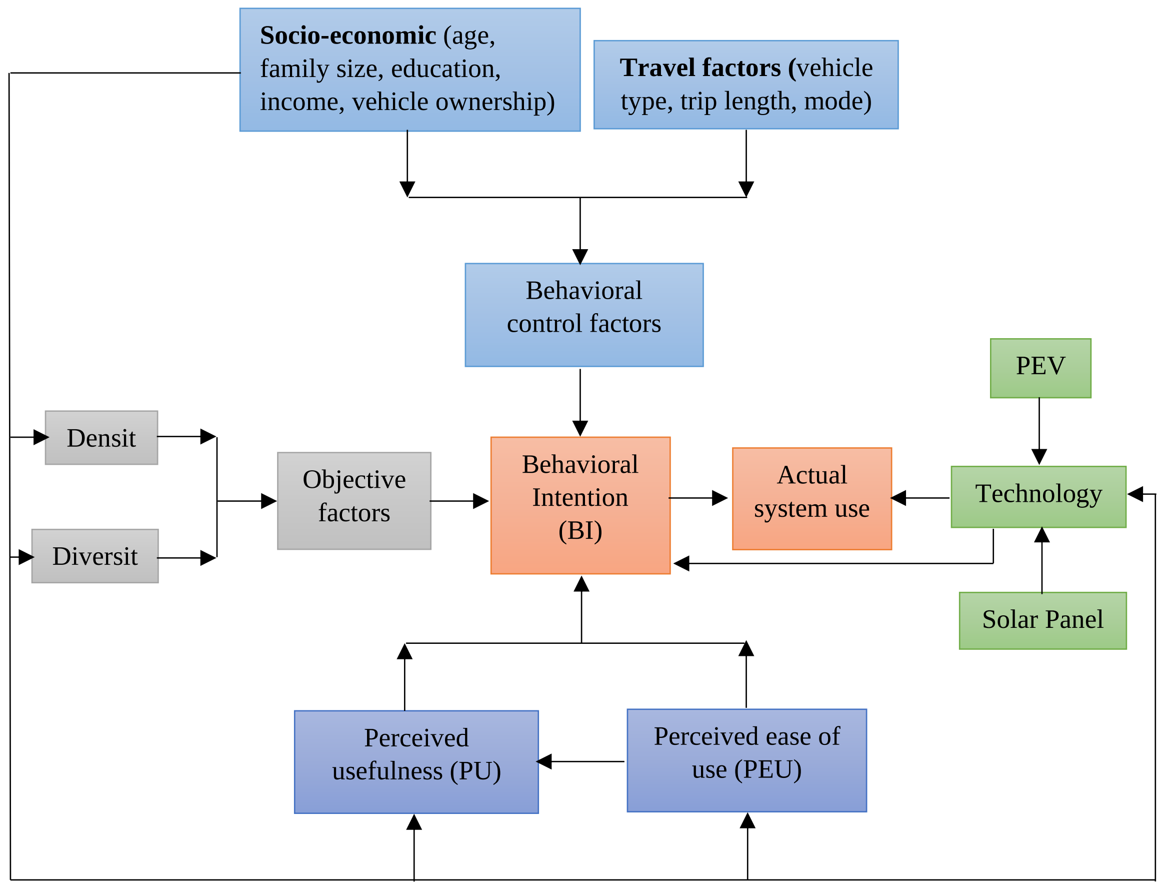


Figure 1: Integrated Technology Acceptance Model (ITAM)

According to the ITAM, human BI towards actual SAV use is directly influenced by behavioral control factors, objective factors, and psychological factors. Additionally, the model posits that the actual use of SAVs also depends on the availability of novel technology such as EV, solar panel and people’s affinity towards new technologies. Besides direct effects, socioeconomic factors also have indirect effect on SAV use by moderating objective factors, psychological factors, and the affinity of the people towards a technology.

The following hypotheses are formulated to address the research questions based on the extant literature and the conceptual framework of ITAM.

a) Socioeconomic and demographic factors

1) Young and working-age adults are positively associated with BI to use SAVs (Hypothesis 1).
2) Family households are negatively associated with BI to use SAVs (Hypothesis 2).
3) Education attainment is positively associated with BI to adopt SAVs (Hypothesis 3).
4) People with employment status and higher household income are less interested to use SAVs compared to their counterparts (Hypothesis 4).

b) The built environment

1) High population and employment density are positively associated with BI to use SAVs (Hypothesis 5).
2) Mixed land uses are positively associated with BI to use SAVs (Hypothesis 6).
3) Neighborhoods with a higher share of zero-vehicle households are more conducive to SAV use (Hypothesis 7).

c) Travel factors

1) People who drive alone to work are less likely to use SAVs (Hypothesis 8).
2) Preference for ride-hailing and ride-sharing services is positively associated with BI to adopt SAVs (Hypothesis 9).
3) People who prefer public transport for their daily travel purposes are more likely to use SAVs (Hypothesis 10).

d) Psychological factors associated with SAVs

1) Perceived usefulness, safety, and effectiveness are positively related to BI to use SAVs (Hypothesis 11).

2) People having familiarity with advanced automated technologies are more likely to use SAVs (Hypothesis 12).
3) Employment status, income, and education positively influence the psychological attributes of people to use SAVs (Hypothesis 13).

e) Technological development

1) Experience with alternative fuel vehicles (e.g., electric vehicles, hybrid electric vehicles, fuel cell vehicles) is positively associated with BI to use SAVs (Hypothesis 14).
2) Employment status, high income, and education level are positively related to the technological preference of people to adopt SAV (Hypothesis 15).

## 3. Research design

### 3.1 Data

To understand the factors that influence people's inclination to adopt SAVs as a transportation mode, this study uses data from the 2019 California Vehicle Survey conducted by the California Energy Commission (California Energy Commission, 2022; Transportation Secure Data Center, 2019). The main purposes of the survey were to assess transportation fuel needs and provide key policy guidelines for transportation planning in California. The survey assessed consumer preferences for light-duty vehicles (both personal and commercial) in the context of expanding autonomous and electric vehicle technologies. It collected economic and demographic data, vehicle information including vehicle and fuel types, and vehicle choice information using a stated preference approach. Moreover, charging behavior, electricity rates, and main motivations for purchasing EVs were collected from the EV owners. The survey instrument includes questions pertaining to perceptions, opinions, intentions, and motivations of people toward self-driving cars and ride-sharing facilities.

This study uses only the online-based residential survey portion of the data. It includes a total of 4,248 responses, which encompass 718 responses by EV owners. A stratified random sampling technique was used to collect data from six regions across the state: San Francisco, Sacramento, Central Valley, Los Angeles, San Diego, and the rest of the state. Households were selected randomly by address at the county level and invited to participate in the survey in such a way to ensure that samples are proportional to the population of each county.

Some data were also collected from the American Community Survey (US Census Bureau, 2018), Environmental Protection Agency (Environmental Protection Agency, 2020), and California State Association of Counties (California State Association of Counties, 2019). These county-level data were then combined with the 2019 California Vehicle Survey as measures of the socioeconomic and demographic environment of each respondent and of their built environment. Finally, the data were processed (i.e., missing value imputation with the median values, creation of new variables from the original data) and analyzed to test the research hypotheses. Detailed description of the variables used in the study is given in Table 1.

Table 1: Description of the variables

| Variable | Variable Description | Measure | Source |
|---|---|---|---|
| Dependent variable | | | |
| AV_POOL | Unlikely to use shared driverless services with strangers | 1 = Strongly agree, 2 = Somewhat agree, 3 = Somewhat disagree, and 4 = Strongly disagree | CVS |
| Independent variables | | | |
| AGE1 | Age of the respondent between 18 and 64 years | 1 = Yes, 0 = No | CVS |
| PHEV | Willingness to consider PHEV only vehicle | 1 = Yes, 0 = No | CVS |
| BEV | Willingness to consider BEV only vehicle | 1 = Yes, 0 = No | CVS |
| PFCEV | Willingness to consider PFCEV only vehicle | 1 = Yes, 0 = No | CVS |
| PUB2 | Use of public transportation (e.g., bus, light rail/tram/subway, and commuter train) for trips in the local area | 1 = Yes, 0 = No | CVS |
| RH2 | Use of ride-hailing services (e.g., Taxi, Uber/Lyft, Uberpool/Lyftline) for trips in the local area | 1 = Yes, 0 = No | CVS |
| RS2 | Use of ride-sharing services for trips in the local area | 1 = Yes, 0 = No | CVS |
| AV_AW | Familiarity of the respondent with AVs | 1 = Never heard, 2 = Heard but not familiar, 3 = heard and somewhat | CVS |

| | | | |
|---|---|---|---|
| | | familiar, and 4 = heard and very familiar | |
| AV1 | AVs would enable the respondent to enjoy traveling more (e.g., watch the scenery, rest) | 1 = Strongly disagree, 2 = Somewhat disagree, 3 = Somewhat agree, and 4 = Strongly agree | CVS |
| AV2 | People would miss the joy of driving and be in control | | CVS |
| AV3 | People would accept longer travel times so the AV could drive at a low speed to prevent unsafe situations for pedestrians and bicyclists | | CVS |
| AV5 | People would reduce time at the regular workplace and work more in the AVs | | CVS |
| AV6 | People would send an empty AV to pick up/drop off their child | | CVS |
| AV7 | People would be able to travel more often even when they are tired, sleepy, or under the influence of alcohol/medications | | CVS |
| RACE3 | Asian population in the county | % | ACS |
| HHI2 | Households with $25,000 to $49,999 income in past 12 months in the county | % | ACS |
| HHI5 | Households with $100,000 and more income in past 12 months in the county | % | ACS |
| POPDEN | Population density in the county | People/km2 | ACS |
| EDU5 | Population 25 years and over with bachelor's or above degree in the county | % | ACS |
| PCI | Per capita income in the past 12 months in the county | $ | ACS |
| LF | Population 16 years and over in the labor force in the county | % | ACS |
| MHV | Median value of the occupied housing units in the county | $ | ACS |
| MY | Median year of housing units in the county | Year | ACS |
| BR1 | Housing units with no bedroom in the county | % | ACS |
| BR2 | Housing units with 1 bedroom in the county | % | ACS |
| FHH | Family households in the county | % | ACS |
| HHS4 | Family households of 5 and more persons in the county | % | ACS |
| MTW1 | Workers 16 years and over who drive alone to work in the county | % | ACS |
| MTW2 | Workers 16 years and over who choose to carpool to commute in the county | % | ACS |
| D1D | Gross activity density (employment + HUs) in the county | (emp.+HUs)/acre | EPA |
| R_PCT | Low wage workers in a CBG (home location) in 2017 in the county | % | EPA |
| PCT | Zero-car households in CBG in 2018 in the county | % | EPA |
| EVR | Registered Republican Voters in 2019 in the county | % | CSAC |
| GDP | Gross Domestic Product per capita in 2018 in the county | $/per capita | CSAC |

PHEV = Plug-in Hybrid Electric Vehicle, BEV = Battery Electric vehicle, PFCEV = Plug-in Fuel Cell Electric Vehicle, CVS = 2019 California Vehicle Survey, ACS = American Community Survey, EPA = Environmental Protection Agency, and CSAC = California State Association of Counties.

Tables 2 and 3 report the characteristics of the respondents, households, and counties in California by outlying the descriptive statistics of dependent and independent variables used in model building. Asking their intentions to use SAVs, the survey found that about 34.40% and

32.60% of respondents are strongly unlikely and somewhat unlikely, respectively, to use SAVs for their daily travel. In contrast, about 10.50% and 22.60% of respondents are strongly and somewhat interested to use SAVs for their daily travel.

Table 2: Descriptive statistics of the variables (N= 4,248)

| Variable | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|
| EDU5 | 12.05 | 58.79 | 34.98 | 10.06 |
| RACE3 | 0.00 | 35.85 | 15.34 | 9.14 |
| HHI2 | 11.57 | 28.83 | 18.22 | 3.66 |
| HHI5 | 13.20 | 56.38 | 37.06 | 9.69 |
| PCI | 17,590.00 | 69,275.00 | 36,800.41 | 9,748.39 |
| LF | 35.12 | 73.08 | 63.85 | 3.50 |
| MHV | 133,300.00 | 1,009,500.00 | 551,136.55 | 199,935.60 |
| MY | 1942.00 | 1991.00 | 1973.10 | 9.08 |
| FHH | 47.87 | 79.90 | 68.62 | 4.92 |
| BR1 | 0.90 | 14.92 | 4.15 | 2.47 |
| BR2 | 5.47 | 25.81 | 13.67 | 4.47 |
| HHS4 | 5.83 | 30.51 | 19.17 | 3.94 |
| MTW1 | 32.94 | 81.81 | 73.59 | 7.81 |
| MTW3 | 0.00 | 34.22 | 5.11 | 5.78 |
| GDP | 36,309.27 | 210,532.00 | 80,843.83 | 36,843.50 |
| EVR | 4.87 | 41.69 | 18.65 | 6.57 |
| PCT | 0.00 | 22.00 | 4.08 | 2.99 |
| R_PCT | 15.00 | 36.00 | 20.92 | 2.88 |
| D1D | 0.01 | 27.12 | 6.94 | 3.92 |
| POPDEN | 0.60 | 7066.04 | 741.81 | 1072.17 |

Table 3: People's socioeconomic features and opinions on technology and AVs (N= 4,248)

| Variable | Measure | Percent |
|---|---|---|
| AGE1 | No | 34.70 |
| | Yes | 65.30 |
| PHEV | No | 53.15 |
| | Yes | 46.85 |
| BEV | No | 64.83 |
| | Yes | 35.17 |
| PFCEV | No | 86.42 |
| | Yes | 13.58 |
| PUB2 | No | 64.74 |
| | Yes | 35.26 |
| RH2 | No | 54.24 |
| | Yes | 45.76 |
| RS2 | No | 92.75 |
| | Yes | 7.25 |
| AV_AW | Never heard | 4.47 |
| | Heard but was not familiar | 38.21 |
| | Heard and somewhat familiar | 43.06 |
| | Heard and very familiar | 14.27 |
| AV1 | Strongly disagree | 22.72 |
| | Somewhat disagree | 19.33 |

| | | |
|---|---|---|
| | Somewhat agree | 39.76 |
| | Strongly agree | 18.20 |
| AV2 | Strongly disagree | 11.80 |
| | Somewhat disagree | 19.60 |
| | Somewhat agree | 37.30 |
| | Strongly agree | 31.40 |
| AV3 | Strongly disagree | 23.73 |
| | Somewhat disagree | 23.07 |
| | Somewhat agree | 36.68 |
| | Strongly agree | 16.53 |
| AV5 | Strongly disagree | 46.00 |
| | Somewhat disagree | 28.63 |
| | Somewhat agree | 19.87 |
| | Strongly agree | 5.51 |
| AV6 | Strongly disagree | 61.06 |
| | Somewhat disagree | 19.11 |
| | Somewhat agree | 14.67 |
| | Strongly agree | 5.16 |
| AV7 | Strongly disagree | 28.27 |
| | Somewhat disagree | 19.35 |
| | Somewhat agree | 35.19 |
| | Strongly agree | 17.18 |
| AV_POOL | Strongly disagree | 10.50 |
| | Somewhat disagree | 22.60 |
| | Somewhat agree | 32.60 |
| | Strongly agree | 34.40 |

Thus, the survey reveals that about one-third of the respondents are interested to adopt and use SAVs in California. The California Department of Motor Vehicles (DMV) has already developed regulations for the manufacturers to follow during testing and before the deployment of AVs on the roads to encourage innovation and promote safety (Department of Motor vehicles, 2021). The California DMV first permitted Nuro, a robotics company, to test AVs on public roads in 2017 and they got approval from DMV to deploy AVs for commercial use on some streets in the Bay Area in December 2020 (Klar, 2020). Consequently, Nuro is already operating AVs in partnership with 7-Eleven to deliver convenience store products (Hawkins, 2021). Currently, more than fifty robotics and auto companies are permitted to test full AVs in California including Waymo and General Motors (Subin & Wayland, 2021). It is expected that AVs would be common on the streets of California in a few years and people would use AVs for their daily travel purposes. Thus, a study investigating people's perceptions, and the factors that influence people to adopt and use AVs is appropriate and timely.

## 3.2 Methods

A Structural Equation Model (SEM) is employed to find the factors that affect peoples' BI toward AVs using the theoretical and conceptual framework described in Figure 1. SEM is popularly used by researchers in psychology and biological sciences, transportation, business, and environmental studies to unveil complex relationships between dependent and independent variables by introducing mediators (Bayard & Jolly, 2007; Irfan et al., 2020; Janggu et al., 2014; Scherer et al., 2019). As a powerful multivariate modeling approach, SEM combines several statistical tools such as regression, factor analysis, and path analysis, to study causal relationships between dependent and independent variables (Shen et al., 2016; Wang et al., 2016). The main strengths of SEM include (1) calculating interceding indirect effects of predictors on outcome variables, (2) estimating total effects through direct and indirect effects, and (3) estimation of the relationship between latent constructs and their manifest factors (Van Acker et al., 2007; Wang et al., 2016). Moreover, SEM shows existing theories in a structural model wherein all the relationships are explicitly specified and estimated (Rahman et al., 2021; Wang et al., 2016).

Eight latent constructs are generated based on Exploratory Factor Analysis (EFA) and extant theories. The constructed model is verified with a Confirmatory Factor Analysis (CFA). Lastly, a path analysis is performed to evaluate the relationships between outcome variable, mediator, and predictors accounting for socioeconomic features. Several fit measures (e.g., chi-square, RMSEA, CFI, TLI) are employed to verify the robustness of the model. The model is calibrated with MPlus Version 7.4 (Muthén & Muthén, 2017). To estimate the model with a categorical (ordinal) dependent variable, this study uses the Weighted Least Squares Means and Variance Adjusted (WLSMV) estimation approach.

## 4. Results

### 4.1. Calibrated model

The overall calibrated model is shown in Figure 2. Several non-significant relations are omitted to attain a robust model. The final estimated model includes interactions between predictors and outcome variable through mediators. In Figure 2, the observed variables are denoted by rectangles and circles indicate latent dimensions. It is worth mentioning that several factors fitting our conceptual model were dropped from the final model after testing to achieve the best-fit final model. These include factors of the built environment (e.g., activity density, workers per household, percent of high wage workers, jobs within 45 minutes of auto travel time), transportation and travel behavior factors (e.g., gas price, percentage of workers who choose public transport to work), technological factor (e.g., the experience of solar panel), and socioeconomic factors (e.g., per capita gross domestic product, household size). Several variables (e.g., population and employment density, land-use diversity, VMT, the share of registered democrat supporters, per capita income) are long-transformed to linearize the relationships captured in the model.

The overall fit of the estimated model is assessed based on several goodness-of-fit indices (Table 5.4). All fit indices are within the acceptable range and thus satisfy the model requirements and confirm the model validity (Hu & Bentler, 1999; MacCallum et al., 1996; Rahman et al., 2020).

Table 4: Goodness-of-fit indices of the calibrated model

| Indices | Recommended value | Value |
|---|---|---|
| Chi-Square | Lower values indicate a better fit | 29,348.32 |
| TLI (Tucker Lewis Index) | 0 to 1, 1 suggests a perfect fit | 0.57 |
| CFI (Comparative Fit Index) | 0 to 1, 1 suggests a perfect fit | 0.52 |
| RMSEA (Root Mean Square Error of Approximation) | <0.05 indicates a very good fit (threshold level is 0.10) | 0.11 |

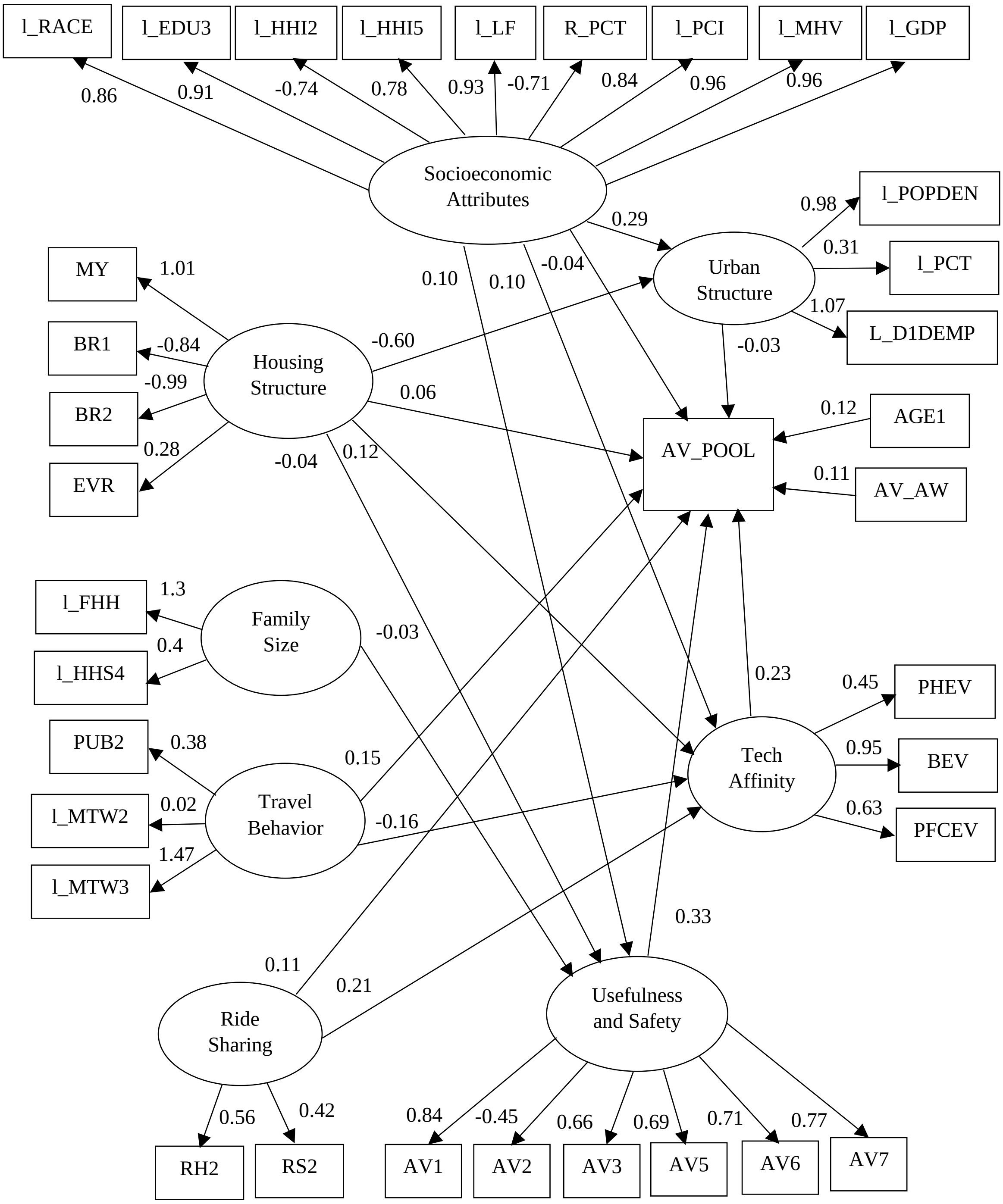


Figure 2: Calibrated model with direct standardized effects

4.2 Standardized direct effects on the intention to use SAVs

The standardized coefficients of the calibrated SEM and the direction of modeled direct effects are given in Table 5. These coefficients indicate the direct associations between and among predictors, outcome variables, and latent dimensions. It indicates that most of the associations are statistically significant at the 0.00, 0.01, or 0.05 levels. However, some of the interactions with a P-value above 0.05 are kept to better understand the model and demonstrate a complete relationship.

Table 5: Estimated standardized direct effects (N= 4,248)

| Relationship between observe/estimated variables and latent factors | | | Estimate | Z | P |
|---|---|---|---|---|---|
| l_RACE3 | ← | Socioeconomic Attributes | 0.86 | 152.99 | 0.00 |
| l_EDU5 | ← | Socioeconomic Attributes | 0.91 | 300.46 | 0.00 |
| l_HHI2 | ← | Socioeconomic Attributes | -0.74 | -150.96 | 0.00 |
| l_HHI5 | ← | Socioeconomic Attributes | 0.78 | 151.43 | 0.00 |
| l_LF | ← | Socioeconomic Attributes | 0.93 | 203.73 | 0.00 |
| R_PCT | ← | Socioeconomic Attributes | -0.71 | -147.47 | 0.00 |
| l_PCI | ← | Socioeconomic Attributes | 0.84 | 213.68 | 0.00 |
| l_MHV | ← | Socioeconomic Attributes | 0.96 | 344.64 | 0.00 |
| l_GDP | ← | Socioeconomic Attributes | 0.96 | 261.27 | 0.00 |
| MY | ← | Housing Structure | 1.01 | 245.74 | 0.00 |
| BR1 | ← | Housing Structure | -0.84 | -188.47 | 0.00 |
| BR2 | ← | Housing Structure | -0.99 | -230.33 | 0.00 |
| EVR | ← | Housing Structure | 0.89 | 152.44 | 0.00 |
| l_FHH | ← | Family Size | 1.32 | 54.43 | 0.00 |
| l_HHS4 | ← | Family Size | 0.43 | 34.58 | 0.00 |
| l_POPDEN | ← | Urban Structure | 0.98 | 166.76 | 0.00 |
| l_PCT | ← | Urban Structure | 0.31 | 34.98 | 0.00 |
| l_D1D | ← | Urban Structure | 1.07 | 237.68 | 0.00 |
| AV1 | ← | Usefulness and Safety | 0.84 | 96.05 | 0.00 |
| AV2 | ← | Usefulness and Safety | -0.45 | -29.58 | 0.00 |
| AV3 | ← | Usefulness and Safety | 0.66 | 57.79 | 0.00 |
| AV5 | ← | Usefulness and Safety | 0.69 | 60.05 | 0.00 |
| AV6 | ← | Usefulness and Safety | 0.71 | 57.05 | 0.00 |
| AV7 | ← | Usefulness and Safety | 0.77 | 77.90 | 0.00 |
| PUB2 | ← | Travel Behavior | 0.45 | 26.42 | 0.00 |
| l_MTW1 | ← | Travel Behavior | -0.76 | -177.50 | 0.00 |
| l_MTW2 | ← | Travel Behavior | 0.96 | 272.56 | 0.00 |
| RH2 | ← | Ride Sharing | 1.10 | 12.70 | 0.00 |
| RS2 | ← | Ride Sharing | 0.51 | 11.69 | 0.00 |
| PHEV | ← | Tech Affinity | 0.45 | 12.23 | 0.00 |
| BEV | ← | Tech Affinity | 0.95 | 17.22 | 0.00 |
| PFCEV | ← | Tech Affinity | 0.63 | 15.95 | 0.00 |
| Urban Structure | ← | Socioeconomic Attributes | 0.29 | 49.68 | 0.00 |
| Urban Structure | ← | Housing Structure | -0.60 | -113.80 | 0.00 |
| Tech Affinity | ← | Socioeconomic Attributes | 0.09 | 2.67 | 0.01 |
| Tech Affinity | ← | Housing Structure | 0.12 | 2.85 | 0.00 |
| Tech Affinity | ← | Travel Behavior | 0.16 | 2.99 | 0.00 |
| Tech Affinity | ← | Ride Sharing | 0.21 | 6.61 | 0.00 |
| Usefulness and Safety | ← | Socioeconomic Attributes | 0.09 | 4.83 | 0.00 |
| Usefulness and Safety | ← | Housing Structure | -0.04 | -2.16 | 0.03 |
| Usefulness and Safety | ← | Family Size | -0.03 | -2.02 | 0.04 |
| AV_POOL | ← | Socioeconomic Attributes | -0.04 | -1.52 | 0.13 |
| AV_POOL | ← | Housing Structure | 0.06 | 1.95 | 0.05 |
| AV_POOL | ← | Urban Structure | -0.03 | -1.38 | 0.17 |
| AV_POOL | ← | Usefulness and Safety | 0.33 | 21.56 | 0.00 |

| | | | | | |
|---|---|---|---|---|---|
| AV_POOL | ← | Travel Behavior | 0.15 | 3.97 | 0.00 |
| AV_POOL | ← | Ride Sharing | 0.11 | 4.90 | 0.00 |
| AV_POOL | ← | Tech Affinity | 0.23 | 9.94 | 0.00 |
| AV_POOL | ← | AV_AW | 0.11 | 7.03 | 0.00 |
| AV_POOL | ← | AGE1 | 0.12 | 7.69 | 0.00 |

Eight latent dimensions are created based on observed and calculated variables.

1) Socioeconomic Attributes: l_RACE3, l_EDU5, l_HHI2, l_HHI5, l_LF, R_PCT, l_PCI, l_MHV, and l_GDP
2) Housing Structure: MY, BR1, BR2, EVR
3) Family Size: l_FHH and l_HHS4
4) Travel Behavior: PUB2, l_MTW1, and l_MTW2
5) Ride-sharing: RH2 and RS2
6) Urban Structure: l_POPDEN, l_PCT, and l_D1D
7) Perceived Usefulness and Safety: AV_1, AV_2, AV_3, AV_5, AV_6, AV_7
8) Tech Affinity: PHEV, BEV, and PFCEV

We now proceed to examine the estimated relationships between observed or estimated independent variables and each of the latent dimensions in the model successively in the context of the hypotheses laid out in Section 2.2.4.

Socioeconomic Attributes: This exogenous latent dimension represents the socioeconomic status of the people in the study area. As indicated in Table 5, this latent dimension is negatively associated with AV_POOL, which indicates that people living in areas with a higher number of highly educated individuals, household income, labor force participation, and Asian identity are less interested in using SAVs. However, the relationship is of marginal statistical significance (P-value of 0.13). Also, I find that this latent dimension is positively associated with the latent dimensions of tech affinity and perceived usefulness and safety of AVs. Thus, people in the higher socioeconomic strata have a greater affinity for Alternative Fuel Vehicles (AFVs) (i.e., EVs) and consider AVs as useful and safe.

Housing Structure: This exogenous latent dimension represents the physical features of the housing units in the study context. As indicated in Table 5, it is positively associated with AV_POOL, which indicates that people living in housing units with more than one bedroom and built after the 1970s, and located in an area with a higher share of republican voters are interested in using SAVs, after controlling for other factors.

Family Size: This exogenous latent dimension is positively associated with l_FHH and l_HHS4 (Table 5). The table also indicates that family size is negatively associated with the perceived usefulness and safety of AVs. Thus, people living in areas with a higher share of family household are concerned about the usefulness, convenience, and safety features of AVs due to the uncertainty and insecurity of family members associated with AVs, but no direct effect on the intention to use SAVs is found.

Urban Structure: This endogenous latent dimension represents the patterns of the built environment. It is positively associated with l_POPDEN, l_PCT, and l_D1D (Table 5). The calibrated model in Figure 2 indicates that urban structure has a negative direct effect on AV_POOL, which indicates that people who live in urban areas with high population and activity density and where car ownership is lower are less likely to use SAVs. The possible explanation lies in the fact that high quality public transportation services in the urban areas could dissuade people from using SAVs. Moreover, people living in such communities would prefer to walk or use bicycles in the urban areas where activities are in closer proximity and reachable in a short travel time. Thus, people in these urban environments are less likely to use SAVs despite the enormous convenience and usefulness of AVs.

Travel Behavior: This exogenous latent dimension denotes people's travel pattern and is created from PUB2, l_MTW1, and l_MTW2. It has a positive association with PUB2 and l_MTW2 and negatively associated with l_MTW1 (Table 5). It is also noticed that travel behavior is positively associated with AV_POOL. Thus, the people who use public transportation for local travel and carpool to work would also likely use SAVs. On the other hand, the people who drive alone to work are less likely to use SAVs.

Ride Sharing: This exogenous latent dimension denotes people's ride sharing status. As it is positively associated with both of the observed variables (RH2 and RS2), the study finds that shared mobility is characterized by the use of different ride-hailing (e.g., Taxi, Uber/Lyft, Uberpool/Lyftline) and ride-sharing services (e.g., bike-share, Car2Go, ZipCar, Jump) for trips in the local area. Table 5 denotes that ride sharing is positively associated with AV_POOL (0.11). All other things held constant, a one-unit increase in ride-sharing services increases people's intentions to use SAVs by 0.11 units. Thus, people's tendency to use ride-sharing services with family and friends significantly increases their willingness to use SAVs.

Perceived Usefulness and Safety: This endogenous latent factor is the only latent dimension that represents convenience, usefulness, and safety features of AVs. As indicated in Table 5, people enjoy traveling (i.e., watching scenery) by AVs, do multitasking while traveling by AVs, and accept longer travel time by AVs to ensure the safety of pedestrians and bicyclists. On the other hand, people would miss the joy of driving. Figure 2 reveals that perceived usefulness and safety are positively associated with AV_POOL (0.33). Other things being constant, a one-unit increase in perceived usefulness and safety increases people's willingness to use SAVs by 0.33 units. Thus, perceived enjoyment and usefulness and perceived lower risk for pedestrians, bicyclists, kids, and themselves have a greater role in motivating people to use SAVs. In contrast, fear and apprehension of losing control of the vehicle they ride in would dissuade people to use SAVs. A higher magnitude of the effect indicates that this latent dimension has a greater role in influencing the intention of people to use SAVs. Thus, psychological factors associated with AVs have a much greater power to influence the willingness of people to share AVs compared to socioeconomic features, and the factors of transportation and of the built environment.

Tech Affinity: This endogenous latent dimension explains people's tech affinity and their willingness to consider AFVs as their travel mode. It encompasses three observed variables (PHEV, BEV, and PFCEV) and is positively associated with the willingness of the respondents to consider PHEV, BEV, and PFCEV in their future purchases (Table 5). The calibrated model in Figure 2 shows that tech affinity has a significant direct positive impact on AV_POOL (0.23). All other things held identical, a one-unit increase in people's tech affinity increases their willingness to use SAVs by 0.23 units. Thus, people who have prior experience of EVs and who are interested in advanced AV technologies have a much higher tendency to use SAVs (Chen, 2019; Shin et al., 2015).

The calibrated model in Figure 2 also indicates that people's familiarity with AVs (AV_AW) is positively associated with their intention to use SAVs (0.11). Thus, a one-unit increase in people's familiarity with AVs increases their willingness to use SAVs by 0.11 units, all other things being held equal. The people who have prior knowledge of AVs are more likely to use SAVs with strangers compared to the people who have little knowledge of AVs or have never heard of them. The California vehicle survey indicates that about 57.33% of respondents have heard about AVs; hence it is assumed that these people would be willing to use SAVs. Thus, prior knowledge about AVs is considered one of the main factors that would influence people toward AVs, as mentioned in previous studies (Hilgarter & Granig, 2020; Laidlaw et al., 2018; Webb et al., 2019). Similarly, the model also explains that working-age people (aged between 18 and 64 years) are positively associated with AV_POOL (0.12). A one-unit increase in the working-age population increases SAV use with strangers by 0.12 units, all other things being held equal. Thus, the working-age people are more interested to use SAV due to their interest in public transportation and shared mobility. Perceived usefulness of AVs further induces working-age people to use SAVs.

4.3 Standardized total effects on the intention to use SAVs

A number of latent factors have both direct and indirect effects on the use of SAVs. For a full account of the reasons for SAV adoption, the total effects of these latent factors can readily be calculated from the SEM estimates. They are presented in Table 6, taking into account direct and indirect effects which are not explicitly mentioned in Figure 2.

Table 6: Standardized total (direct and indirect) effects of latent factors on AV purchase

| Effects of latent factors on AV purchase | | | Direct | Indirect | Total |
|---|---|---|---|---|---|
| AV_POOL | ← | Socioeconomic Attributes | -0.04 | 0.04 | 0.01 |
| AV_POOL | ← | Travel Behavior | 0.15 | 0.04 | 0.18 |
| AV_POOL | ← | Ride Sharing | 0.11 | 0.05 | 0.16 |
| AV_POOL | ← | Family Size | -- | -0.01 | -0.01 |
| AV_POOL | ← | Housing Structure | 0.06 | 0.03 | 0.09 |

As specified in Table 6, socioeconomic attributes have direct and indirect effects on people's willingness to use SAVs by mediating urban structure, tech affinity, and perceived usefulness and safety of AVs. Considering both direct and indirect effects, the socioeconomic attributes have a total effect of 0.01 on sharing AVs with strangers. People living in areas with high socioeconomic status of households are interested to use SAVs due to their affinity to advanced technologies, improved AV amenities, and neighborhood selection in the areas with high population and activity density. However, the magnitude of this total effect is minimal and insignificant. Similarly, the housing structure has a total effect of 0.09 including direct and indirect effects through urban structure, tech affinity, and perceived usefulness and safety of AVs. On the other hand, family size only has an indirect effect of -0.01, mediating the perceived usefulness and safety of AVs. The magnitude of this effect is minimal. Table 6 also indicates that housing structure has greater effects on SAV use compared to socioeconomic attributes and family structure.

Travel behavior has a total effect of 0.18 consisting of direct and indirect effects by mediating people's tech affinity. Similarly, considering direct and indirect effects through tech affinity, ride sharing has a total effect of 0.16 on sharing AVs with strangers. Thus, people's tendency to use public transportation, carpool, ride-hailing, and ride-sharing services significantly increase their intention to use SAVs with family, friends, and even strangers. People's travel mode choice behaviors remain the most influential factor in deciding SAV use after accounting for the built environment attributes, the physical structure of housing units, and socioeconomic features. Thus, people's preference for public transportation and other ride-sharing services are the key factors to increase SAV adoption.

## 5. Discussion

The study found that many people are already aware of AVs and services provided by AVs in California. People consider that riding AVs is enjoyable, safe, and effective, although some of them would not send empty AVs to drop off or pick up their children due to insecurity and uncertainty. Nevertheless, many people are interested in using SAVs due to their prior experience with EVs and higher tendency to use public transportation and shared mobility options. Also, the California state government has already introduced regulations to test and operate AVs. Consequently, many people would be interested to use SAVs. However, appropriate strategies (e.g., onboard driver, incentives, collaboration with transport network companies, conducive built environment, and institutional framework) should be implemented to encourage people to use SAVs (Etminani-Ghasrodashti et al., 2021; Feys et al., 2020).

Results from the SEM indicate that people residing in areas with a higher share of highly educated individuals, household income, labor force participation, and Asian identity are less interested to use SAVs, which supports hypothesis 4 runs contrary to hypothesis 3. Accounting for indirect effects, it is also observed that people living in areas with high socioeconomic status have an interest in AVs due to their tech affinity and perceived usefulness and safety of AVs. Thus, it could be argued that although people with high education and income are less interested in SAVs, they are more interested to use private AVs which echoed the findings of previous studies (Lavieri & Bhat, 2019; Wang et al., 2020). The results also indicate that young and working-age adults would be favorably inclined to use SAVs due to their interest in cutting-edge technologies and shared mobility, and financial ability, which supports hypothesis 1.

Similarly, people living in areas with larger and newer housing units are more interested to use SAVs. The possible explanation lies in the fact that people living in larger and new housing have a greater consumption capability and are willing to use private SAVs, considering the convenience and usefulness associated with AVs. Although family size has no direct effect on SAVs, the indirect effect indicates that people living in the context with a higher share of family households are less interested to use SAVs due to uncertainty, breach of privacy, and safety issues associated with AVs which conforms with previous studies (Hao et al., 2019; Krueger et al., 2016) and supports hypothesis 2. Overall, socioeconomic attributes, housing structure, and family size illustrating the study context have limited influence on the BI of people to use SAVs.

The study also estimated that people who live in urban areas with a higher population and activity density and a higher share of household with no car are less likely to use SAVs, which contradicts hypotheses 5, 6, and 7. The results challenge the findings from previous studies where researchers demonstrated that urban people would be more interested to use SAVs (Barbour et al., 2019; Lavieri & Bhat, 2019; Merfeld et al., 2019). The possible explanation lies in the fact that people in urban areas where activities are closely located would prefer to walk or use bicycles instead of using SAVs. Another possible explanation is that people who live in urban areas have higher household income. Therefore, considering better services offered by AVs, they could use private AVs compared to SAVs which indicates the multifarious effect of household income. Moreover, a supportive built environment (e.g., ramp, appropriate pick-up and drop-off points) could further motivate people to use SAVs including the people with mobility challenges (Etminani-Ghasrodashti et al., 2021). Overall, the factors of the built environment have little power to govern people’s BI to use SAVs.

Study results also showed that people who prefer public transportation, car-sharing, ride-hailing, and ride-sharing services for daily travel purposes are more likely to use SAVs. In contrast, people who drive alone to work are less likely to use SAVs. The findings agree with hypotheses 8, 9, and 10 and support previous studies (Asgari et al., 2018; Lavieri & Bhat, 2019; Zhou et al., 2020). Also, people's travel behaviors and ride-sharing attitudes are the most influential factor to influence BI to use SAVs after accounting for socioeconomic features, family structure, the built environment, and transportation and psychological factors associated with AVs. Thus, people's perceptions of shared mobility are one of the key factors in households' intention to use SAVs. Integration of SAVs with existing on-demand ride-sharing services and identifying concerns, preferences, and expectations of potential users could be practical strategies to motivate people to use SAVs (Etminani-Ghasrodashti et al., 2021).

The study also found that perceived enjoyment, usefulness, and safety significantly influence people to use SAVs. On the other hand, people who enjoy driving are less likely to use SAVs due to fear of losing control of vehicles. Thus, psychological features of AVs significantly influence people's BI to use SAVs compared to socioeconomic features, housing structure, transportation factors, and the built environment. The study also observes that the people who have prior knowledge about AVs are more likely to use SAVs compared to the people who have little knowledge of them or have never heard of AVs and never used an EVs. Additionally, people with high affordability and education are positive about the usefulness and convenience of AVs. These findings sustain hypotheses 11, 12, and 13 and align well with the conclusions from previous studies (Hao et al., 2019; Merfeld et al., 2019; Yuen et al., 2020). The study also found that people's prior experience of using alternative fuel vehicles (e.g., electric vehicles, hybrid electric vehicles, fuel cell vehicles) significantly motivates people to use SAVs (accept hypothesis 14). Moreover, people with high income and education level have a greater affinity for advanced technology, which further motivates them to use SAVs (accept hypothesis 15).

## 6. Conclusions and future research agenda

This study significantly contributes to the literature by empirically investigating the prominent determinants of people's intentions to use SAVs. The study findings can be helpful for transportation agencies, professionals, stakeholders, and AV developers to formulate relevant policies for designing and implementing SAVs. Since many people are already aware of AVs, some effective measures could increase the willingness of people to use SAVs. Appropriate initiatives should be implemented by transit agencies and other transport providers (i.e., transport network companies, bike-sharing companies) to facilitate SAVs, which are environmentally friendly and ensure multimodal transportation (Cohen et al., 2017; Narayanan et al., 2020; Sparrow & Howard, 2017). The ride-hailing and ride-sharing companies could pioneer the launch of SAVs and let the people have the real-world experience of this efficient and novel transportation mode.

Through coordination with public transit agencies, SAVs can be implemented to solve the last-mile problem and thereby increase transit ridership and reduce transportation costs (Moorthy et al., 2017; Sparrow & Howard, 2017). Planning agencies could implement several policy actions such as designated lanes for SAVs, priority curb space for SAVs in urban areas, and a higher posted speed of SAVs to ensure equity and motivate people to use SAVs (Cohen et al., 2017). Since many people already have their cars, they would be less interested to use SAVs. However, implementing some strategies such as playing music or movie of people's choice, recommending some driving routes based on users' travel history, and customized interior lighting and design could be implemented to develop psychological ownership to induce them to use SAVs (Lee et al., 2019).

Despite insightful findings, the strengths of this study are shattered by some cautionary limitations. I identify hereunder some priority extensions of the present work:

1) This research should be replicated in other states to establish the robustness of the model and compare possible variability under different cultural, socioeconomic, and political contexts.
2) To understand the effects of the built environment, data related to the built environment aggregated at a finer granularity in the geographic unit (e.g., block group, census tract) should be used in future studies.
3) As the technology context change quickly, and given the strong dependence of intentions formulation on knowledge and experience of AVs technologies, a longitudinal analysis would be invaluable to more cogently articulate the criticality of certain decision points in the shaping of opinions and better estimate when societal acceptability may become pervasive.
4) The impacts of different opportunities (e.g., low congestion, emission) and challenges (e.g., legal aspect, breach of privacy, system failure) related to AVs, and institutional arrangement (e.g., incentives, regulations) are not evaluated in this study, which requires further investigation.
5) Future studies should investigate the equity aspects of SAV among different income and racial groups to ensure justice in transportation.

## References

Adjei, E., & Behrens, R. (2012). Travel behaviour change theories and experiments: a review and synthesis. *SATC 2012*.

Ajzen, H., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. Prentice-Hall.

Ajzen, I. (1985). *From intentions to actions: A theory of planned behavior*. Springer.

Asgari, H., Jin, X., & Corkery, T. (2018). A stated preference survey approach to understanding mobility choices in light of shared mobility services and automated vehicle technologies in the US. *Transportation Research Record, 2672*(47), 12-22.

Bamberg, S. (2006). Is a residential relocation a good opportunity to change people's travel behavior? Results from a theory-driven intervention study. *Environment and behavior*, *38*(6), 820-840.

Bamberg, S., Ajzen, I., & Schmidt, P. (2003). Choice of travel mode in the theory of planned behavior: The roles of past behavior, habit, and reasoned action. *Basic and applied social psychology*, *25*(3), 175-187.

Barbour, N., Menon, N., Zhang, Y., & Mannering, F. (2019). Shared automated vehicles: A statistical analysis of consumer use likelihoods and concerns. *Transport Policy*, *80*, 86-93.

Bayard, B., & Jolly, C. (2007). Environmental behavior structure and socio-economic conditions of hillside farmers: A multiple-group structural equation modeling approach. *Ecological Economics*, *62*(3-4), 433-440.

California Energy Commission. (2022). *California Vehicle Survey*. https://www.energy.ca.gov/data-reports/surveys/california-vehicle-survey

California State Association of Counties. (2019). *California County Data Pile*, https://www.counties.org/post/datapile

Cartenì, A. (2020). The acceptability value of autonomous vehicles: A quantitative analysis of the willingness to pay for shared autonomous vehicles (SAVs) mobility services. *Transportation Research Interdisciplinary Perspectives*, *8*, Article 100224.

Chan, N. D., & Shaheen, S. A. (2012). Ridesharing in North America: Past, present, and future. *Transport Reviews*, *32*(1), 93-112.

Chen, C.-F. (2019). Factors affecting the decision to use autonomous shuttle services: Evidence from a scooter-dominant urban context. *Transportation research part F: traffic psychology and behaviour*, *67*, 195-204.

Cohen, S., Shirazi, S., & Curtis, T. (2017). *Can we advance social equity with shared, autonomous and electric vehicles* (Institute of Transportation Studies at the University of California, Davis, Issue. C. G. s. O. o. P. a. Research. https://www.transformca.org/sites/default/files/3R.Equity.Indesign.Final_.pdf

Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results* Massachusetts Institute of Technology]. https://dspace.mit.edu/handle/1721.1/15192

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: a comparison of two theoretical models. *Management science*, *35*(8), 982-1003.

Department of Motor vehicles. (2021). *Autonomous Vehicle Deployment Program*. California, US: California Department of Transportation Retrieved from https://www.dmv.ca.gov/portal/vehicle-industry-services/autonomous-vehicles/autonomous-vehicle-deployment-program/

Environmental Protection Agency. (2020). *Smart Location Mapping*, https://www.epa.gov/smartgrowth/smart-location-mapping\#SLD

Etminani-Ghasrodashti, R., Patel, R. K., Kermanshachi, S., Rosenberger, J. M., Weinreich, D., & Foss, A. (2021). Integration of shared autonomous vehicles (SAVs) into existing transportation services: a focus group study. *Transportation Research Interdisciplinary Perspectives*, *12*, Article 100481.

Fagnant, D. J., & Kockelman, K. M. (2018). Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas. *Transportation*, *45*(1), 143-158.

Feys, M., Rombaut, E., & Vanhaverbeke, L. (2020). Experience and Acceptance of Autonomous Shuttles in the Brussels Capital Region. *Sustainability*, *12*(20), Article 8403.
Fisbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behavior: An introduction to theory and research*. Addison-Wiley Publishing Company.
Fishbein, M., & Ajzen, I. (1977). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Addison-Wiley Publishing Company.
Golbabaei, F., Yigitcanlar, T., & Bunker, J. (2021). The role of shared autonomous vehicle systems in delivering smart urban mobility: A systematic review of the literature. *International Journal of Sustainable Transportation*, *15*(10), 731-748.
Gurumurthy, K. M., & Kockelman, K. M. (2020). Modeling Americans' autonomous vehicle preferences: A focus on dynamic ride-sharing, privacy & long-distance mode choices. *Technological Forecasting and Social Change*, *150*, Article 119792.
Hao, M., Li, Y., & Yamamoto, T. (2019). Public preferences and willingness to pay for shared autonomous vehicles services in Nagoya, Japan. *Smart cities*, *2*(2), 230-244.
Hawkins, A. J. (2021). *California is getting its first real autonomous delivery service thanks to Nuro and 7-Eleven*. Vox Media. https://www.theverge.com/2021/12/1/22810674/nuro-7-eleven-autonomous-vehicle-delivery-california
Heath, Y., & Gifford, R. (2002). Extending the theory of planned behavior: Predicting the use of public transportation1. *Journal of Applied Social Psychology*, *32*(10), 2154-2189.
Hilgarter, K., & Granig, P. (2020). Public perception of autonomous vehicles: a qualitative study based on interviews after riding an autonomous shuttle. *Transportation research part F: traffic psychology and behaviour*, *72*, 226-243.
Hu, J.-W., & Creutzig, F. (2022). A systematic review on shared mobility in China. *International Journal of Sustainable Transportation*, *16*(4), 374-389.
Hu, L. t., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a multidisciplinary journal*, *6*(1), 1-55.
Irfan, M., Zhao, Z.-Y., Li, H., & Rehman, A. (2020). The influence of consumers' intention factors on willingness to pay for renewable energy: a structural equation modeling approach. *Environmental Science and Pollution Research*, *27*(17), 21747-21761.
Janggu, T., Darus, F., Zain, M. M., & Sawani, Y. (2014). Does good corporate governance lead to better sustainability reporting? An analysis using structural equation modeling. *Procedia-Social and Behavioral Sciences*, *145*, 138-145.
Klar, R. (2020, December 24, 2020). California grants first permit for commercial use of self-driving cars to Nuro. *The Hill*. https://thehill.com/policy/technology/531592-california-grants-first-permit-for-commercial-use-of-self-driving-cars-to
Krueger, R., Rashidi, T. H., & Rose, J. M. (2016). Preferences for shared autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *69*, 343-355.
Laidlaw, K., Sweet, M., & Olsen, T. (2018). Forecasting the outlook for automated vehicles in the Greater Toronto and Hamilton Area using a 2016 consumer survey. *Retrieved on September*, *3*, 2018.
Lavieri, P. S., & Bhat, C. R. (2019). Modeling individuals' willingness to share trips with strangers in an autonomous vehicle future. *Transportation Research Part A: Policy and Practice*, *124*, 242-261.
Lavieri, P. S., Garikapati, V. M., Bhat, C. R., Pendyala, R. M., Astroza, S., & Dias, F. F. (2017). Modeling individual preferences for ownership and sharing of autonomous vehicle technologies. *Transportation Research Record*, *2665*(1), 1-10.
Lee, J., Lee, D., Park, Y., Lee, S., & Ha, T. (2019). Autonomous vehicles can be shared, but a feeling of ownership is important: Examination of the influential factors for intention

to use autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *107*, 411-422.
Lee, Y., Kozar, K. A., & Larsen, K. R. (2003). The technology acceptance model: Past, present, and future. *Communications of the Association for information systems*, *12*(1), 50.
MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological methods*, *1*(2), 130.
Machado, C. A. S., De Salles Hue, N. P. M., Berssaneti, F. T., & Quintanilha, J. A. (2018). An Overview of Shared Mobility. *Sustainability*, *10*(12), 4342.
Madden, T. J., Ellen, P. S., & Ajzen, I. (1992). A comparison of the theory of planned behavior and the theory of reasoned action. *Personality and social psychology Bulletin*, *18*(1), 3-9.
Maeng, K., & Cho, Y. (2022). Who will want to use shared autonomous vehicle service and how much? A consumer experiment in South Korea. *Travel Behaviour and Society*, *26*, 9-17.
Mara, M., & Meyer, K. (2022). Acceptance of autonomous vehicles: An overview of user-specific, car-specific and contextual determinants. *User Experience Design in the Era of Automated Driving*, 51-83.
McKenzie, G. (2020). Urban mobility in the sharing economy: A spatiotemporal comparison of shared mobility services. *Computers, Environment and Urban Systems*, *79*, 101418.
Menon, N., Barbour, N., Zhang, Y., Pinjari, A. R., & Mannering, F. (2018). Shared autonomous vehicles and their potential impacts on household vehicle ownership: An exploratory empirical assessment. *International Journal of Sustainable Transportation*, *13*(2), 111-122.
Merfeld, K., Wilhelms, M.-P., Henkel, S., & Kreutzer, K. (2019). Carsharing with shared autonomous vehicles: Uncovering drivers, barriers and future developments–A four-stage Delphi study. *Technological Forecasting and Social Change*, *144*, 66-81.
Moorthy, A., De Kleine, R., Keoleian, G., Good, J., & Lewis, G. (2017). Shared Autonomous Vehicles as a Sustainable Solution to the Last Mile Problem: A Case Study of Ann Arbor-Detroit Area. *SAE International Journal of Passenger Cars - Electronic and Electrical Systems*, *10*(2), 328-336.
Morris, J., Marzano, M., Dandy, N., & O'Brien, L. (2012). *Theories and models of behaviour and behaviour change*. http://www.forestry.gov.uk/pdf/behaviour_review_theory.pdf/$FILE/behaviour_review_theory.pdf
Muthén, B., & Muthén, L. (2017). *Mplus*. Chapman and Hall/CRC.
Narayanan, S., Chaniotakis, E., & Antoniou, C. (2020). Shared autonomous vehicle services: A comprehensive review. *Transportation Research Part C: Emerging Technologies*, *111*, 255-293.
Paddeu, D., Shergold, I., & Parkhurst, G. (2020). The social perspective on policy towards local shared autonomous vehicle services (LSAVS). *Transport Policy*, *98*, 116-126.
Rahman, M., Thill, J.-C., & Paul, K. C. (2020). COVID-19 pandemic severity, lockdown regimes, and people's mobility: Early evidence from 88 countries. *Sustainability*, *12*(21), Article 9101.
Rahman, M. M., Lesch, M. F., Horrey, W. J., & Strawderman, L. (2017). Assessing the utility of TAM, TPB, and UTAUT for advanced driver assistance systems. *Accident Analysis & Prevention*, *108*, 361-373.
Rahman, M. M., Najaf, P., Fields, M. G., & Thill, J.-C. (2021). Traffic congestion and its urban scale factors: Empirical evidence from American urban areas. *International Journal of Sustainable Transportation*, 1-16, Article 1885085.

Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education*, *128*, 13-35.

Shen, W., Xiao, W., & Wang, X. (2016). Passenger satisfaction evaluation model for Urban rail transit: A structural equation modeling based on partial least squares. *Transport Policy*, *46*, 20-31.

Shin, J., Bhat, C. R., You, D., Garikapati, V. M., & Pendyala, R. M. (2015). Consumer preferences and willingness to pay for advanced vehicle technology options and fuel types. *Transportation Research Part C: Emerging Technologies*, *60*, 511-524.

Sparrow, R., & Howard, M. (2017). When human beings are like drunk robots: Driverless vehicles, ethics, and the future of transport. *Transportation Research Part C: Emerging Technologies*, *80*, 206-215.

Stocker, A., & Shaheen, S. (2018). Shared automated mobility: early exploration and potential impacts. *Road vehicle automation 4*, 125-139.

Subin, S., & Wayland, M. (2021). *Alphabet's Waymo and GM's Cruise get California DMV approval to run commercial autonomous car services*. NBCUniversal News Group. https://www.cnbc.com/2021/09/30/waymo-and-cruise-get-california-dmv-approval-to-run-driverless-cars.html

The World Bank. (2007). *Theories of Behavior Change, Communication for Governance and Accountability Program (CommGAP)*. http://siteresources.worldbank.org/EXTGOVACC/Resources/BehaviorChangeweb.pdf

Transportation Secure Data Center. (2019). *2019 California Vehicle Survey*. www.nrel.gov/tsdc

US Census Bureau. (2018). *American Community Survey*, https://www.census.gov/programs-surveys/acs/about.html

Van Acker, V., Witlox, F., & Van Wee, B. (2007). The effects of the land use system on travel behavior: a structural equation modeling approach. *Transportation planning and technology*, *30*(4), 331-353.

Wang, S., Jiang, Z., Noland, R. B., & Mondschein, A. S. (2020). Attitudes towards privately-owned and shared autonomous vehicles. *Transportation research part F: traffic psychology and behaviour*, *72*, 297-306.

Wang, Y., Han, Q., De Vries, B., & Zuo, J. (2016). How the public reacts to social impacts in construction projects? A structural equation modeling study. *International Journal of Project Management*, *34*(8), 1433-1448.

Webb, J., Wilson, C., & Kularatne, T. (2019). Will people accept shared autonomous electric vehicles? A survey before and after receipt of the costs and benefits. *Economic Analysis and Policy*, *61*, 118-135.

Yuen, K. F., Huyen, D. T. K., Wang, X., & Qi, G. (2020). Factors influencing the adoption of shared autonomous vehicles. *International journal of environmental research and public health*, *17*(13), Article 4868.

Zhang, T., Tao, D., Qu, X., Zhang, X., Zeng, J., Zhu, H., & Zhu, H. (2020). Automated vehicle acceptance in China: Social influence and initial trust are key determinants. *Transportation Research Part C: Emerging Technologies*, *112*, 220-233.

Zhou, F., Zheng, Z., Whitehead, J., Washington, S., Perrons, R. K., & Page, L. (2020). Preference heterogeneity in mode choice for car-sharing and shared automated vehicles. *Transportation Research Part A: Policy and Practice*, *132*, 633-650.