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Research Article

Private or on-demand autonomous vehicles? Modeling public interest using a multivariate model

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ABSTRACT: With the likely future of autonomous vehicles (AVs) as private, ride-hailing, and pooled vehicles, it is important to consider all forms of AVs when estimating the impacts of automation on travel behavior. To aid this, this study jointly models the public interest in three forms of AVs (owning, ride-hailing, and using pooled services) and compares the interests in owning versus ride-hailing AVs using a combination of structural equation modeling and multivariate ordered probit modeling frameworks. Using the 2019 California Vehicle Survey data, we estimate the impacts of several exogenous and latent variables on all forms of AV adoption. We find that the individual, household, travel-related, and built-environment factors are related to different forms of AV adoption directly and indirectly through attitudes toward human and automated driving. We also report that human and automated driving sentiments have the highest impact on interest in owning an AV compared to interest in ride-hailing and using pooled AVs. We discuss several policy implications by calculating the pseudo-elasticity effects of exogenous variables and the sensitivities of the impacts on latent variables on different forms of AV adoption. For example, public interest in owning private AVs can be increased by more than 7% by making them familiar with autonomous technology.

KEYWORDS: autonomous vehicles (AVs), on-demand or shared services, adoption interest, sentiment, multivariate ordered probit model

1 Introduction

Over the last decade, the transportation industry, academia, and media worlds have been considering the concept of autonomous vehicles (AVs) as a promising solution to the current negative externalities of transportation. It is believed that the AVs—that utilize the combination of global positional systems (GPS), light detection and ranging (LIDAR), and machine learning applications to enable self-driving abilities (Kaplan et al., 2019)—will improve overall traffic safety (Ye and Yamamoto, 2019), mobility (Coppola and Silvestri, 2019), accessibility and equity (Cohn et al., 2019), and environmental efficiency (Kopelias et al., 2020) of the transportation system despite the concerns related to equipment and system safety performance (Acharya and Humagain, 2022), higher cost (Emory et al., 2022), data privacy and security (Acharya and Mekker, 2022a, 2022b), and legal liabilities (Alawadhi et al., 2020). In addition to these, a huge shift in travel behavior, especially the mode choice, travel-based activities, and travel patterns, is expected (Dannemiller et al., 2021). This revolutionary shift in travel behavior with the arrival of AVs is possible because these vehicles will not only replace the current human-driven vehicles (HVs), but they will be equally available as on-demand vehicles (ride-hailing and pooled AV services). Although it still takes some years to decades to have fully AVs widespread in the real world, it is necessary to understand the public intention towards adoption, purchase, and use of this new technology, its impacts on travel behavior, and prepare well ahead to shape its future. Because of the potential future of AVs as private, ride-hailing, and pooled vehicles, it is equally important to consider these all forms of AV adoption when estimating the impacts of AVs on travel behavior.

This study jointly models the public interest in three forms of AVs: owning an AV, ride-hailing in an AV, and using pooled AVs, and directly compares the interests in owning an AV versus ride-hailing in an AV. Since different levels of automation exist, this study defines AVs as fully self-driving vehicles that do not require manual driving efforts, also described as SAE automation level 5 (SAE International, 2021). The possible correlations among the adoption interests of different forms of AVs, caused by common unobserved factors, are explicitly considered in the joint model. Two sets of variables are considered to impact all forms of AVs: exogenous and attitudinal variables. Exogenous variables include individual socio-demographics, household demographics, travel-related characteristics, built environment characteristics, and some other miscellaneous characteristics. Hypothesizing that not all the variances in the public interest in AV adoption are explained by the above-stated exogenous variables, we consider two attitudinal variables—pro-AV and pro-HV sentiments—that potentially explain the differences in public interest towards AV adoption. We define pro-AV and pro-HV sentiments as the variables that describe individuals' positive attitudes towards favoring automated and human driving, respectively. These variables are latent, meaning that multiple items or indicators are used to define the variables.

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The modeling framework employed in this study is presented in Fig. 1. The framework consists of two stages. In the first stage, the attitudinal latent variables—pro-AV sentiment and pro-HV sentiment—are modeled using measurement and structural equation models. The measurement model links the observed indicators with the unobserved latent variables, whereas the structural equation model uncovers the relationships between exogenous and latent variables. The predicted values of the latent variables estimated in the measurement model are used in the second stage. Thus, in the second stage, a multivariate ordered probit model is fitted by considering two sets of predictors: (1) exogenous variables, which include individual socio-demographics, household socio-demographics, travel-related characteristics, and built-environment characteristics, and (2) two latent variables related to attitudes on automated and human driving derived from the observed indicators. Ideally, better estimates could be obtained by modeling both models—measurement and multivariate ordered probit—simultaneously. However, a two-stage modeling framework is adopted at the cost of reducing the computational burden. In fact, measurement errors can be significantly minimized by increasing the sample size (Ben-Akiva et al., 2002), and this study has a relatively larger sample size of 4,136. In addition, the use of the two-stage modeling approach is further supported by the findings of Raveau et al. (2010), where only a small improvement in model fit is reported when two-stage modeling is replaced by simultaneous modeling compared to the cost of the increased computational burden.

Research on the modeling of public interest in different forms of AVs is plentiful in the literature. To follow the literature in this domain, please refer to the recent review articles: Alwadhi et al. (2020), Becker and Axhausen (2017), Duarte and Ratti (2018), Gkartzonikas and Gkritza (2019), Golbabaei et al. (2020), Kaye et al. (2021), Keszey (2020), and Othman (2021). Most of the studies in the literature, relatable to the present study, are dedicated to uncovering factors affecting the interest in one or multiple forms of AVs. These studies have a common consensus that individual demographics, household characteristics, travel behaviors, built-environment characteristics, and personal attitudes impact the interests in one or multiple forms of AV adoption. This empirical study primarily contributes to the existing literature in the following three ways.

1) We distinguish and jointly model the acceptance of AVs in three forms: interests in owning an AV, ride-hailing in an AV, and using pooled AV, and compare the interests in owning an AV versus ride-hailing in an AV. Most past studies either did not consider all these forms of AVs or focused only on one/some forms of AVs. Also, the direct comparison between public interests in owning an AV vs. ride-hailing in an AV, as in this study, is rarely made in the past study. To our knowledge, only Xiao and Goulias (2022), utilizing the same dataset, have considered all these four outcome variables.

2) We account for the taste heterogeneity in three forms of AV adoption (owning, ride-hailing, using pooled services) and interests in owning an AV vs. ride-hailing in an AV by considering the latent variables explaining the attitudes towards automated and human driving. In fact, we consider two latent variables: pro-AV and pro-HV sentiments, which are not fully considered in Xiao and Goulias (2022) though the dataset allows them. By doing so, the impacts of latent variables on each form of AV acceptance can be compared to each other. There is a plethora of studies in literature that have considered a variety of latent attitudinal variables as predictors of different forms of AV adoption. Among many, commonly considered latent attitudinal variables are technology savviness/technology interest (Haboucha et al., 2017; Irannezhad and Mahadevan, 2022; Nazari et al., 2018), green travel pattern (Nazari et al., 2018), safety concern (Acharya and Humagain, 2022; Irannezhad and Mahadevan, 2022; Jabbari et al., 2022; Nazari et al., 2018), car ownership importance (Jabbari et al., 2022), environmental concern (Haboucha et al., 2017), enjoy driving (Haboucha et al., 2017), etc. We find few past studies considering pro-AV sentiment (e.g., Haboucha et al., 2017) as a latent attitudinal predictor of AV acceptance, but we are not aware of any past studies considering pro-HV sentiment. We agree that the consideration of pro-AV and pro-HV sentiments alone is not sufficient to accurately model the acceptance of AVs, but this is the best that can be done with this dataset.

3) We conduct two policy analyses—calculate the pseudo-elasticity effects of exogenous variables and sensitivities of the impacts of latent variables on outcome variables—and make several policy implications. In fact, the estimates of the ordered probit model do not allow the direct comparison of estimate coefficients, and thus the policy analyses inform the expected changes in AV adoption interests when the exogenous and latent variables are changed. These types of policy analyses are rarely made in past studies.

The remainder of this paper is organized as follows: Section 2 presents the study methodology, Section 3 describes the data used in the study, Section 4 presents the analyses performed and the results from each analysis with policy implications, and Section 5 discusses the study conclusions and limitations.

2 Methodology

This section presents the methodology adopted in the present

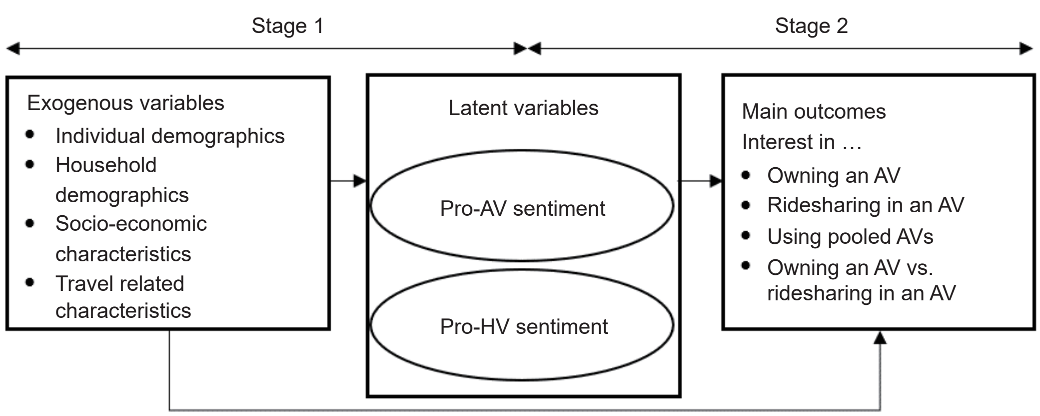

Fig. 1 Research modeling framework.

study. As stated earlier, the modeling of interests in AV adoption is done in two stages. First, the measurement model of latent variables related to the attitudes towards automated and human driving is defined. This formulation along with the structural relationships between latent and exogenous variables are presented in Section 2.1. Section 2.2 is related to the second stage of the research model, where the multivariate ordered probit model of four different AV adoption interests is formulated.

2.1 Measurement and structural equation models of latent variables

A measurement model establishes the connection between unobserved latent variables and observed items. In this study, two latent variables, pro-AV and pro-HV sentiments, are assessed using multiple items. The specification of the measurement model that shows the connections between observed items and latent variables is shown in Eq. (1) (Kline, 2015):

$$\boldsymbol{v}_t = \lambda_t F_l + \boldsymbol{e}_l \tag{1}$$

where $l \in \{1, 2, \ldots, L\}$ and $t \in \{1, 2, \ldots, T\}$ are the indexes of latent variables and observed items such that F_l and $\boldsymbol{v}_t$ represent the vector of latent variables and their respective observed items. λ_t is the vector of parameters that link observed items $\boldsymbol{v}_t$ and latent variables F_l. $\boldsymbol{e}_l$ accounts for the measurement error associated with each latent variable, assuming a standard normal distribution.

The structural equation model establishes the relationships between latent and exogenous variables. In this study, only the impacts of exogenous variables on latent variables are assessed, which is represented by Eq. (2) (Kline, 2015):

$$F_l = B_i \boldsymbol{X}_i + \boldsymbol{r}_l \tag{2}$$

where $i \in \{1, 2, \ldots, I\}$ is the index of exogenous variables such that $\boldsymbol{X}_i$ denotes the vector of exogenous variables and B_i represents their respective parameters that explain their relationships with latent variables F_i. $\boldsymbol{r}_l$ denotes the vector of residuals associated with each latent variable, which is also assumed to be standard normally distributed.

2.2 Multivariate ordered probit model

A multivariate ordered probit model is a generalization of the probit model that models multiple outcome variables of the ordered nature and accounts for the correlations between the variables. In the context of this paper, the outcome variables are four types of AV adoption interests: owning, ride-hailing, using pooled, owning vs. ride-hailing, which are correlated to each other as verified in this study and measured in an ordered Likert scale. This necessitates the use of the multivariate ordered probit model in the present study. The generalized specification of this model, as specified in Greene and Hensher (2010) and Washington et al. (2020), is shown in Eq. (3):

$$Y_i^* = \beta_i' \boldsymbol{X}_i + \varepsilon_i \tag{3}$$

where $i \in \{1, 2, \ldots, I\}$ refers to an outcome variable from a set of I. Y_i^* is an unobserved continuous latent propensity associated with each corresponding outcome variable Y_i. $\boldsymbol{X}_i$ is a vector of covariates (exogenous and latent variables) associated with the outcome variable Y_i. $\boldsymbol{\beta}_i$ is the coefficient vector associated with each covariate X_i for the outcome variable Y_i. ε_i is the error term.

Y_i is an ordered variable having multiple levels. There are K levels in the outcome of variable Y_i, and then there exists $K + 1$ thresholds ($\mu_i^0, \mu_i^1, \mu_i^2, \ldots, \mu_i^{K-1}, \mu_i^K$). The thresholds delimit the intervals of latent propensity Y_i^* based on the observed outcome variable Y_i with two ends of thresholds as ∞ ($\mu_i^0 = -\infty$, $\mu_i^K = \infty$). As an example, the thresholds for the outcome variable Y_i can be defined as shown in Eq. (4):

$$Y_i = \begin{cases} 1, & \mu_i^0 \le Y_i^* \le \mu_i^1 \\ 2, & \mu_i^1 \le Y_i^* \le \mu_i^2 \\ 3, & \mu_i^{K-1} \le Y_i^* \le \mu_i^K \end{cases} \tag{4}$$

In the probit model, the error term $_i$ is assumed to be normally distributed with a mean of 0 and a variance of 1. To account for the correlation between the error structure of multiple outcome variables, the error structure is specified as a combination of the mean and variance-covariance matrix as in Eq. (5):

$$\boldsymbol{\varepsilon} \sim N\left[\begin{pmatrix} 0 \\ 0 \\ \cdots \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{12} & \cdots & \rho_{1I} \\ & 1 & \cdots & \rho_{2I} \\ & & \cdots & \cdots \\ & & & 1 \end{pmatrix}\right] \tag{5}$$

In the variance-covariance matrix part of Eq. (5), ρ'_{ii} $(i \neq i')$ reflect the correlation between the unobserved factors of ordered outcome i and i'. If there exists no correlation between the unobserved factors of outcome variables (i.e., the off-diagonal elements of the variance-covariance matrix are all zero), the model collapses to a set of independent ordered probit models.

For outcome variable Y_i with $k \in \{1, 2, \ldots, K\}$ levels, the probability that $Y_i = k$, conditioned on model parameters β_i, μ_i^{K-1} thresholds, and ρ'_{ii} correlations of errors, can be written as in Eq. (6):

$$P[Y_i = K] = \int_{z_1}\int_{z_2}, \ldots, \int_{z_K} \varphi\left(z_1, z_2 \ldots z_K, \rho_{11}, \rho_{12}, \ldots, \rho_{\mathrm{II}}\right) \mathrm{d}z_1 \mathrm{d}z_2 \ldots \mathrm{d}z_K \tag{6}$$

where the limits of z_1, z_2, …, z_K, are $[\mu_i^0 - \beta_i' X_i, \mu_i^1 - \beta_i' X_i]$, $[\mu_i^1 - \beta_i' X_i, \mu_i^2 - \beta_i' X_i]$, …, $[\mu_i^{K-1} - \beta_i' X_i, \mu_i^K - \beta_i' X_i]$. $\varphi(\cdot)$ is the probability density function. This equation does not have a closed form solution, so simulation is carried out to estimate this model. The coefficient estimates (β_i) obtained from Eq. (6) are used to interpret the highest and lowest levels of the ordered outcomes. That means a positive β_i for X_i implies an increase in the probability of the highest ordered level (K) of the outcome variable Y_i.

3 Data

This study utilizes the data collected from the California Vehicle Survey (CVS; Transportation Secure Data Center, 2019) conducted by the California Energy Commission in 2019. The primary objective of the 2019 CVS was to assess the consumer preferences for various vehicle attributes and to forecast the transportation fuel needs in the state of California (California Vehicle Survey California Energy Commission., 2019). Though the main CVS survey was designed to assess both commercial and residential vehicle ownership preferences, the questions related to the AVs (about attitudes and ownership preferences) were also asked in the residential portion of the survey. Thus, this study uses the residential portion of the CVS data, which consisted of 4,248 observations. It is to be noted that the residential survey was asked at the household level rather than the individual level, mostly to understand the vehicle ownership preferences of the households.

For more information on the questionnaire, survey data, and analysis scripts, please visit this study's open data repository (Acharya, 2022). Section 3.1 presents the outcome (dependent) variables, whereas Sections 3.2 and 3.3 describe the exogeneous (independent) variables and observed indicators of the latent variables describing attitudes on automated and human driving, respectively.

3.1 Outcome variables

The questionnaire consisted of four questions to inquire about the public interest in AV adoption. The wording of the questions and choice categories are presented in Table 1. Based on the question wording, these four questions are hereafter described as interests in owning an AV, ride-hailing in an AV, using pooled AVs, and owning an AV vs. ride-hailing in an AV, respectively. Out of 4,248 observations, 112 observations had missing values for interest in ride-hailing in an AV and were removed. Thus, after cleaning the dataset, the sample consisted of 4,136 observations that were used for analyses. The distribution of the respondents' interests in all forms of AV adoption is presented in Table 1. Overall, around half of the respondents are inclined toward not being interested in all forms of AV adoption. In addition, when asked to choose between owning an AV and ride-hailing in an AV, the respondents are distributed more or less equally.

3.2 Exogenous variables

The exogenous variables considered in the study mainly consist of individual and household socio-demographics, travel-related characteristics, and built environment characteristics which are listed in Table 2. The sample consists of adults only such that the age is at least 18 years. Among them, more than half (52.85%) belong to the 35–64 years age category. The proportion of males (53.05%) is slightly higher than that of females (46.95%). In terms of race, more than two-thirds of the sample (70.41%) are white. The annual household income of almost one-third of the sample (37.71%) lies between \$25,000 and \$75,000. The sample significantly consists of respondents with at least an undergraduate degree such that the proportions of the sample with undergraduate and graduate or higher degrees are 54.55% and 34.60%, respectively. On average, the number of adults (age ≥ 16 years) in the household is 1.98. A small proportion of the sample (4.79%) is students, whereas more than one-third of the sample (38.68%) are unemployed (do not work for pay).

Considering that the adoption of new vehicle technology is dependent upon the existing travel characteristics, some key travel characteristics of the respondents are included in the study. Slightly less than half of the sample (40.93%) drives alone for the commute. The sample has an average one-way commute distance of 8.08 miles and commutes on an average of 2.28 days a week. A significant portion of the sample has a driving license (98.96%). The average household vehicle ownership of the sample is 1.95. More than two-fifths of the sample (42.65%) have never heard of or are not familiar with AVs, whereas another two-fifths is somewhat familiar. More than two-fifths of the sample (43.50%) report being the sole decision-maker in the household to purchase a vehicle. Other than these, descriptive statistics of many other individual socio-demographics, household characteristics, and travel characteristics, including job type, housing type, and experience with different travel modes are reported in Table 2.

3.3 Indicators of latent variables

Considering that the attitudes toward automated and human driving affect the behavioral adoption of AVs, two latent variables—pro-AV and pro-HV sentiments—are treated as the

Table 1 Sample data for public interest in AV adoption

Variable/question/choice	Coding	(#)	(%)
Interest in owning an AV			
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?			
We would wait as long as possible and try to avoid ever buying a self-driving vehicle	1	1,899	45.91
We would eventually buy a self-driving vehicle, but only after they are in common use	2	1,871	45.24
We would be one of the first to buy a self-driving vehicle (either as a replacement or additional household vehicle)	3	366	8.85
Interest in ride-hailing in an AV			
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?			
Keep current vehicles and not use any driverless services	1	1,728	41.78
Keep current vehicles, but also use these driverless services whenever needed or convenient	2	2,033	49.15
Get rid of one (or more) household vehicles and use driverless ride-hailing services instead	3	375	9.07
Interest in using pooled AVs*			
Please choose the response that best expresses your opinion on the following statement: I would be unlikely to use shared driverless services (even at lower cost) because I would not want to share a vehicle with strangers.			
Strongly agree	1	1,422	34.38
Somewhat agree	2	1,349	32.62
Somewhat disagree	3	942	22.78
Strongly disagree	4	423	10.23
Interest in owning an AV vs. ride-hailing in an AV			
Overall, what would be your relative interest in owning a driverless vehicle versus using on-demand ride-hailing services?			
Much more interested in using on-demand driverless services	1	505	12.21
Somewhat more interested in using on-demand driverless services	2	1,472	35.59
Somewhat more interested in owning a driverless vehicle	3	1,481	35.81
Much more interested in owning a driverless vehicle	4	678	16.39

Note: * reverse coded for analysis.

Table 2 Sample data for individual and household characteristics

Variable	(#)	(%)	Variable	(#)	(%)
Age			Income		
18–34 years	510	12.33	Less than $24,999	241	5.83
35–64 years	2,186	52.85	$25,000 to $74,999	1,146	37.71
65+ years	1,440	34.82	$75,000 to $149,999	1,383	33.44
Region			$150,000 or more	1,004	24.27
Central Valley	242	5.85	Prefer not to answer	362	8.75
Los Angeles	1,870	45.21	Gender		
Rest of state	326	7.88	Male	2,194	53.05
San Diego	384	9.28	Female/other	1,942	46.95
San Francisco	974	23.55	Employment		
Sacramento	337	8.15	Full-time	1,809	43.74
Do not know	3	0.07	Part-time	389	9.41
Vehicle purchase decision role			Both full- and part-time	19	0.46
Sole decision maker	1,799	43.50	Do not work for pay	1,600	38.68
Primary decision maker	1,046	25.29	Self-employed	319	7.71
Share equal roles with others	1,291	31.21	Student		
# of household vehicles*	1.95	0.99	Full-time	78	1.89
# of households*			Part-time	59	1.43
< 5 years old	0.10	0.39	Full- or part-time online	61	1.47
5–11 years old	0.13	0.43	Not currently enrolled	3,938	95.21
12–16 years old	0.09	0.34	Education		
≥ 16 years old	1.98	0.83	Less than high school	33	0.80
Experience with work/school shuttle			High school or equivalent graduate	416	10.06
Not familiar/not available/never use	3,973	96.06	Some college, college, or equivalent graduate	2,256	54.55
Available and use it	163	3.94	Higher than a graduate degree	1,431	34.60
Experience with public bus			Driving license		
Not familiar/not available/never use	3,445	83.29	Yes	4,093	98.96
Available and use it	691	16.71	No	43	1.04
Experience with light rail/tram/subway			Drive frequency		
Not familiar/not available/never use	3,227	78.02	Every day	3,158	76.35
Available and use it	909	21.98	Once or twice a week	859	20.77
Experience with commuter train			Once a month or less	63	1.52
Not familiar/not available/never use	3,465	83.78	Never	13	0.31
Available and use it	671	16.22	Job type		
Experience with taxi			One fixed work location	1,739	42.05
Not familiar/not available/never use	3,599	87.02	Work location varies	394	9.53
Available and use it	537	12.98	Work from home	312	7.54
Experience with rental car			Drive/travel for work	91	2.20
Not familiar/not available/never use	2,803	67.77	Transit trips per week*	0.76	4.37
Available and use it	1,333	32.23	Ride-hailing trips per week*	0.34	2.20
Experience with ride-hailing			Commute mode		
Not familiar/not available/never use	2,554	61.75	Drive alone	1,693	40.93
Available and use it	1,582	38.25	Carpool	184	4.45
Experience with shared ride-hailing			Walk, bike	80	1.93
Not familiar/not available/never use	3,335	80.63	Public transit	104	2.51
Available and use it	801	19.37	Other modes	72	1.74
Experience with carsharing			Commute distance (one-way, miles)*	8.08	14.68
Not familiar/not available/never use	4,048	97.87	Commute days per week*	2.28	2.37
Available and use it	88	2.13	School mode		
Experience with Bike sharing			Drive alone	85	2.06
Not familiar/not available/never use	4,033	97.51	Carpool	28	0.68
Available and use it	103	2.49	Walk, bike	9	0.22
Experience with shared eBikes or eScooters			Public transit	9	0.22
Not familiar/not available/never use	3,983	96.30	Other modes	6	0.15
Available and use it	153	3.70	School distance (one-way, miles)*	0.44	4.51

(Continued)

Variable	(#)	(%)	Variable	(#)	(%)
Experience with peer-to-peer car rental			Ethnicity: Hispanic, Latino, or Spanish origin		
Not familiar/not available/never use	4,051	97.94	Yes	407	9.84
Available and use it	85	2.06	No	3,729	90.16
AV familiarity			Ethnicity and race		
Never heard/not familiar	1,764	42.65	American Indian or Alaska Native	86	2.08
Heard and somewhat familiar	1,780	43.04	Asian	626	15.14
Heard and very familiar	592	14.31	Black or African American	152	3.68
Housing			Native Hawaiian or other Pacific Islander	34	0.82
Not-attached single-family house	2,794	67.55	White	2,912	70.41
Attached single-family house	363	8.78	Other	169	4.09
Mobile house	98	2.37	Prefer not to answer	304	7.35
Building with 2–4 apartments	196	4.74			
Building with 5–19 apartments	295	7.13			
Building with ≥ 20 apartments	363	8.78			
Boat, recreational vehicle, van, etc.	9	0.22			
Other	18	0.44			

Note: * indicates continuous variables, and the mean and standard deviation values are reported instead of (#) and (%) for such variables, respectively.

predictors of interests in owning an AV, ride-hailing in an AV, using pooled AVs, and owning an AV vs. ride-hailing in an AV in this study. Seven indicators or survey items on a 5-point Likert scale are used to measure two unobserved latent variables. Out of seven items, two items are related to the perception of traveling more and accepting longer travel time in an AV, and three items are related to attitude on potential AV advantages: working in-vehicle, traveling even when fatigued, and using AV to pick/drop children without adult supervision. The remaining two items are related to the overall perception of the need for automation and personal preference for manual driving (i.e., joy of manual driving). The analytical procedure adopted to define the latent variables, i.e., the relationships between the survey items and latent variables, is presented in Section 4.1. The distribution of the responses on the indicators of latent variables is presented in Fig. 2. More than half of the sample enjoy traveling more and accept longer travel time in an AV. In terms of potential AV advantages, more than half of the sample is confident about using AVs to travel even when fatigued and under alcohol influence, but only around one-quarter of the sample is confident about working in an AV and using AVs to escort their child. Though the sample is almost equally divided on the positive and negative perceptions of automation, only around one-third of the sample would not miss the joy of manual driving in the AV era.

4 Analyses and results

In this section, we report the analyses and associated results. Sections 4.1 and 4.2 present the estimated results of the measurement and structural equation models and the multivariate ordered probit model, respectively. Furthermore, the estimation results of the policy analyses (pseudo-elastic effects of exogenous variables and the impacts of latent variables on the outcome variables) are presented in Section 4.3. Finally, the key results of all

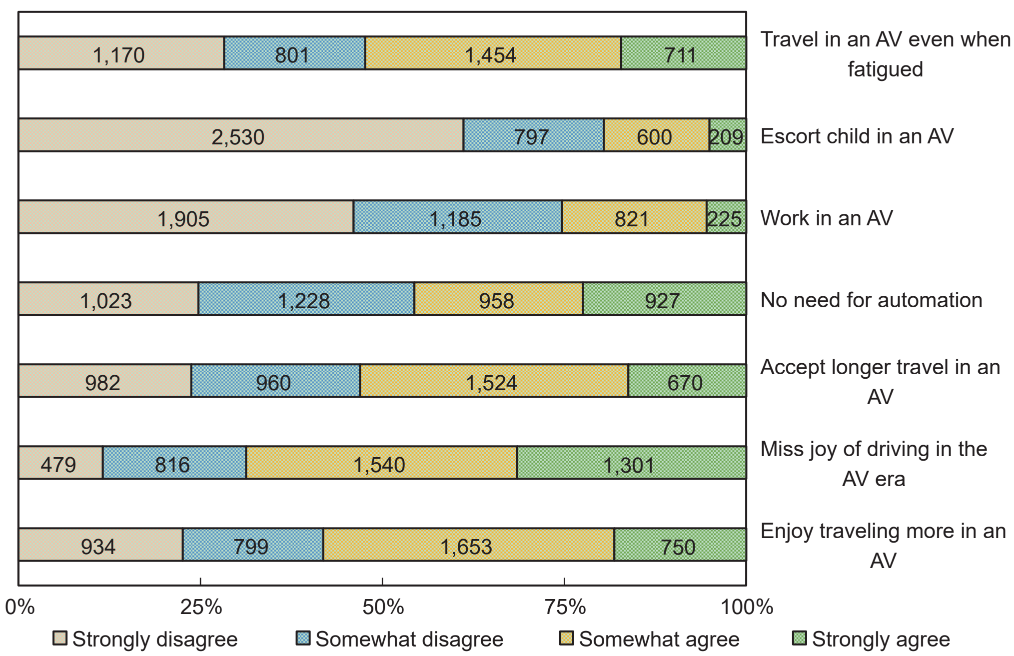

Fig. 2 Sample data for the indicators of latent variables related to attitudes toward automated and human driving.

analyses are discussed in Section 4.4.

4.1 Estimated measurement and structural equation models

The methodological procedures to estimate the measurement and structural equation models involving latent variables are presented in Section 2.1. We fit these models in R (R Core Team, 2022) using the lavaan package (Rosseel, 2012) with a robust variant of the weighted least square estimator developed by Muthén et al. (1997) called weighted least square mean adjusted (WLSM). The estimation results are presented in Table 3. Both models involve two latent variables: pro-AV and pro-HV sentiments.

The measurement model results, presented in Table 3, show that seven indicators (Fig. 2) well define two unobserved latent variables as indicated by statistically significant parameter estimates (with large t-statistics) of indicators on latent variables and the overall model fit indices: chi-square value (degree of freedom = 13) = 400.006 (p-value $\leq$ 0.001), comparative fit index (CFI) = 0.995, root mean square error of approximation (RMSEA) = 0.056, and standardized root mean square residual (SRMR) =

Table 3 Estimation results of measurement and structural equation models

Variable	Pro-AV sentiment		Pro-HV sentiment	
	Coeff	*t*-stat.	Coeff	*t*-stat.
Measurement equation model				
Pro-AV sentiment				
Enjoy traveling more in an AV	0.880	n/a	—	—
Accept longer travel in an AV	0.664	56.669	—	—
Work in an AV	0.691	61.872	—	—
Escort child in an AV	0.717	60.902	—	—
Travel in an AV even when fatigued	0.781	75.250	—	—
Pro-HV sentiment				
Miss joy of driving in the AV era	—	—	0.577	n/a
No need for automation	—	—	0.867	30.552
Structural equation model				
Age				
35–64 years	−0.325	−7.058	0.086	2.276
65+ years	−0.505	−9.141	0.135	3.086
Region				
Rest of state	0.127	2.250	—	n/a
San Francisco	—	n/a	−0.064	−2.278
# of household vehicles	−0.049	−3.145	0.037	3.08
# of households				
5–11 years old	0.092	2.574	—	n/a
12–16 years old	0.177	3.944	—	n/a
Experience with public bus: Available and use it	0.167	3.901	−0.114	−3.556
Experience with commuter train: Available and use it	—	n/a	−0.069	−2.104
Experience with rental car: Available and use it	−0.074	−2.189	0.079	3.111
Experience with ride-hailing: Available and use it	0.272	8.003	−0.160	−6.124
Experience with carsharing: Available and use it	0.340	3.068	—	n/a
Experience with peer-to-peer car rental: Available and use it	0.264	2.473	0.162	2.022
AV familiarity				
Heard and somewhat familiar	0.165	4.825	−0.146	−5.722
Heard and very familiar	0.454	9.614	−0.338	−9.393
Income				
$150,000 or more	0.133	3.447	−0.184	−6.153
Prefer not to answer	−0.115	−1.978	—	n/a
Gender: Female/other	−0.146	−4.584	0.069	2.939
Employment: Do not work for pay	—	n/a	0.075	2.658
Education: High school or equivalent graduate	—	n/a	0.149	4.056
Commute mode: Other mode	−0.282	−2.668	—	n/a
Race				
Asian	0.227	5.056	−0.152	−4.431
Prefer not to answer	—	n/a	−0.108	−2.651
R^2 (structural equation model)	0.168		0.165	
# of observations	4,136			

Note: "—" indicates a non-significant parameter (at 95% confidence interval) that is removed from the model, and "n/a" indicates not applicable. Coefficient (Coeff) estimates presented are standardized and unstandardized for measurement and structural equation models, respectively.

0.034. The critical cutoff values of these estimates for a good model fit are CFI ≥ 0.97 (Hu and Bentler, 1999), RMSEA ≤ 0.05 (Browne and Cudeck, 1993), and SRMR ≤ 0.08 (Hu and Bentler, 1999). In addition, though a lower chi-square value with a higher *p*-value indicates good model fit, higher chi-square values are common when the sample size is higher (Bentler and Bonnet, 1980), as is the case in this study. As a result, five measured items: enjoy traveling more in an AV, accept longer travel in an AV, work in an AV, escort child in an AV, and travel in an AV even when fatigued define the pro-AV sentiment, and the remaining two measured items: miss joy of driving in the AV era and no need for automation define the pro-HV sentiment. The results of exploratory factor analysis (EFA) performed before defining the measurement model guide fixing the number of latent variables and the relationships between the measured items and conceptualized latent variables in the measurement model. The results of EFA are presented in Table A1 in Appendix. Based on the fitted measurement model, the values of latent variables are predicted for each individual, which are the inputs in the multivariate ordered probit model of AV adoption presented in Section 4.2.

Once the measurement model is defined, the structural equation model is fitted to ascertain the relationships between exogenous and latent variables. All the individual, household, travel-related, built environment, and other characteristics presented in Table 2 are first considered as the predictors of latent variables, but the variables with non-significant effects are gradually dropped and the final results are presented in Table 3. The fit indices of this model are chi-square value (degree of freedom = 139) = 702.707 (p-value $\leq$ 0.001), CFI = 0.984, RMSEA = 0.026, and SRMR = 0.035. Based on the cutoff criteria for these values, as mentioned above, the model is considered a good fit.

4.2 Estimated multivariate ordered probit model of AV adoption

The methodology presented in Section 2.2 is implemented in R (R Core Team, 2022) using the mvord package (Hirk et al., 2020) to fit the multivariate ordered probit model of AV adoption. Four outcome variables—interests in owning an AV, ride-hailing in an AV, using pooled AVs, and owning an AV vs. ride-hailing in an AV—are jointly estimated by allowing the error components to correlate with each other, with individual, household, travel-related, built environment, and other characteristics and latent variables as predictors, and the results are presented in Table 4. The goodness of fit of the model is confirmed by the higher log-likelihood of the final model (−46,565.17) compared to that of the null model (−54,028.88). As verified from the model results, the error components of the outcome variables are significantly correlated with each other. This suggests that common unobserved factors jointly increase or decrease all forms of AV adoption. The model development starts by considering all individual, household, and travel-related characteristics presented in Table 2 and two latent variables, but the model is finalized by gradually dropping the insignificant predictors. Thus, only the statistically significant estimates are presented in Table 4.

4.3 Policy analyses

The estimates presented in Table 4 are interpretable by the sign (positive or negative) of the coefficients, such that a positive sign indicates an increase in the highest level of interest or a decrease in the lowest level of interest for the respective outcome variable. However, these estimates do not provide a sense of the direction and magnitude of the effects of independent variables on outcome variables. To aid the interpretation of model results for policy implications, we compute the pseudo-elasticity effects of exogenous variables and the impact of the latent variables on the choice probability (similar to Piras et al. (2021)) in Sections 4.3.1 and 4.3.2 respectively.

4.3.1 Pseudo-elasticity effects of independent variables on AV adoption interests

Pseudo-elasticity effects refer to the change in choice probability for each level of the outcome variable after a change in an independent variable. In this study, aggregate-level pseudo-elasticity effects are calculated using Eq. (7):

$$\Delta P\left(Y_{ik}|X_i, X_i'\right) = \frac{1}{N}\sum_{n=1}^{N}\left[P\left(Y_{ik}|X_i'\right) - P\left(Yy_{ik}|X_i\right)\right] \tag{7}$$

where $\Delta P\left(Y_{ik}|X_i, X_i'\right)$ refers to the aggregate change in choice probability of a level $k \in \{1, 2, \ldots, K\}$ of an outcome variable Y_i when a set of independent variables is changed from X_i to X_i'. Within a set of independent variables X_i, only one independent variable of interest is changed, keeping all other independent

Table 4 Estimated multivariate ordered probit model of AV adoption

Variable	Interest in …							
	Owning an AV		Ride-hailing in an AV		Using pooled AVs		Owning an AV vs. ride-hailing in an AV	
	Coeff	*t*-stat.	Coeff	*t*-stat.	Coeff	*t*-stat.	Coeff	*t*-stat.
Exogenous variable								
Age: 35–64 years	−0.315	−5.054	—	n/a	—	n/a	−0.244	−4.521
Age: 65+ years	−0.377	−4.892	—	n/a	−0.118	−3.110	−0.276	−4.644
Region: Rest of state	—	n/a	—	n/a	0.129	1.985	—	n/a
Region: San Francisco	—	n/a	—	n/a	0.145	3.312	—	n/a
Region: Do not know	—	n/a	—	n/a	—	n/a	1.314	1.996
Vehicle purchase decision role: Primary decision maker	—	n/a	0.128	2.450	—	n/a	—	n/a
Vehicle purchase decision role: Share equal role with others	—	n/a	0.110	2.311	—	n/a	—	n/a
# of household vehicles	—	n/a	0.065	3.025	—	n/a	—	n/a
# of households: < 5 years old	—	n/a	—	—	—	n/a	0.144	3.115
Experience with public bus: Available and use it	—	n/a	0.112	2.127	0.191	3.752	—	n/a
Experience with light rail/tram/subway: Available and use it	—	n/a	—	n/a	0.102	2.043	—	n/a

(Continued)

Variable	Interest in … Owning an AV		Ride-hailing in an AV		Using pooled AVs		Owning an AV vs. ride-hailing in an AV	
	Coeff	*t*-stat.	Coeff	*t*-stat.	Coeff	*t*-stat.	Coeff	*t*-stat.
Experience with commuter train: Available and use it	—	n/a	—	n/a	—	n/a	−0.134	−2.967
Experience with rental car: Available and use it	—	n/a	—	n/a	−0.117	−3.032	—	n/a
Experience with ride-hailing: Available and use it	0.136	3.048	0.262	6.088	0.090	2.036	−0.213	−5.157
Experience with shared ride-hailing: Available and use it	—	n/a	—	n/a	0.368	7.110	−0.123	−2.538
Experience with peer-to-peer car rental: Available and use it	—	n/a	−0.492	−3.955	−0.339	−2.627	—	n/a
AV familiarity: Heard and somewhat familiar	0.268	5.697	0.093	2.302	—	n/a	0.158	4.153
AV familiarity: Heard and very familiar	0.567	9.395	—	n/a	—	n/a	0.338	6.640
Housing: Building with ≥ 20 apartments	—	n/a	0.187	2.688	—	n/a	—	n/a
Income: $75,000 to $149,999	0.208	4.337	—	n/a	−0.089	−2.137	—	n/a
Income: $150,000 or more	0.330	5.978	—	n/a	−0.121	−2.552	—	n/a
Gender: Female/other	—	n/a	−0.090	−2.214	−0.070	−1.961	—	n/a
Employment: Both full- and part-time	—	n/a	—	n/a	0.679	2.152	—	n/a
Employment: Do not work for pay	−0.302	−3.564	—	n/a	—	n/a	—	n/a
Education: High school or equivalent graduate	—	n/a	−0.161	−2.371	−0.227	-3.915	—	n/a
Education: Some college, college, or equivalent graduate	—	n/a	−0.113	−2.666	—	n/a	—	n/a
Drive frequency: Once a month or less	−0.442	−2.142	—	n/a	—	n/a	—	n/a
Drive frequency: Never	—	n/a	−0.545	−1.984	—	n/a	—	n/a
Transit trips per week	0.013	3.676	—	n/a	—	n/a	—	n/a
Job type: Work from home	−0.264	−2.439	—	n/a	—	n/a	—	n/a
Commute mode: Carpool	—	n/a	—	n/a	0.229	2.849	—	n/a
Commute mode: Walk, bike	—	n/a	—	n/a	0.322	2.679	−0.287	−2.638
Commute days per week	−0.054	−3.196	—	n/a	—	n/a	—	n/a
Ethnicity: Not Hispanic, Latino, or Spanish origin	−0.192	−3.040	—	n/a	—	n/a	—	n/a
Race: Asian	—	n/a	0.138	2.642	—	n/a	—	n/a
Race: Black or African American	—	n/a	−0.315	−2.977	—	n/a	—	n/a
Race: Prefer not to answer	—	n/a	0.161	2.232	—	n/a	—	n/a
Latent variables								
Pro-AV sentiment	0.790	19.679	0.523	13.026	0.127	3.584	0.155	4.382
Pro-HV sentiment	−1.096	−15.195	−0.924	−13.506	−0.574	−9.823	−0.285	−4.836
Thresholds								
1 | 2	−1.808	−17.280	−0.002	−0.026	−1.434	−29.440	−0.805	−13.559
2 | 3	0.474	4.447	2.022	30.159	−0.527	−11.498	0.295	5.051
3 | 4	n/a	n/a	n/a	n/a	0.425	9.226	1.446	23.469
Correlations								
Intention to …	—	—	—	—	—	—	—	—
Owning an AV	1.000	n/a	—	—	—	—	—	—
Ride-hailing in an AV	−0.315	−16.505	1.000	n/a	—	—	—	—
Using pooled AVs	0.098	4.456	−0.158	−7.514	1.000	n/a	—	—
Owning an AV vs. ride-hailing in an AV	0.292	15.198	0.101	5.066	−0.105	−5.907	1.000	n/a
Goodness-of-fit measures								
Number of observations	4,136							
Log-likelihood of null-model	−54,028.88							
Log-likelihood of full-model	−46,565.17							

Note: "—" indicates a non-significant parameter (at 95% confidence interval) that is removed from the model, and "n/a" indicates not applicable.

variables the same to get X_i'. For calculation, this change in choice probability for a level of an outcome variable Y_{ik} is calculated for each individual $n \in \{1, 2, \ldots, N\}$, and then averaged over the total number of individuals N.

For a continuous independent variable within a set of independent variables X_i, X_i' is obtained by increasing or decreasing the value of the variable by a certain percentage (e.g., 20%) keeping all other variables the same. Whereas, for a categorical variable within a set of independent variables, X_i, X_i' is obtained by changing the levels of categories of interest for the variable, keeping all other variables the same. In doing so, multiple changes in independent variables are possible. However, for brevity, only a change of interest is done for each independent variable and the results are presented in Table 5. It is also to be noted that the change in independent variables impacts the outcome variables indirectly through latent variables in addition to

Table 5 Pseudo-elasticity effects of independent variables on AV adoption interests

Independent variable	Change in independent variable	Outcome variable	Probability of choice of category …			
			1	2	3	4
Age	All individuals are 65+ years.	Owning an AV	4.87%	−2.60%	−2.28%	—
		Ride-hailing in an AV	2.16%	−1.14%	−1.01%	—
		Using pooled AVs	2.97%	0.03%	−1.46%	−1.55%
		Owning an AV vs. Ride-hailing in an AV	1.30%	1.42%	−0.93%	−1.80%
Vehicle purchase decision role	All individuals are sole decision-makers.	Ride-hailing in an AV	1.91%	−0.99%	−0.91%	—
# of household vehicles	Increase by 20%.	Owning an AV	0.39%	−0.22%	−0.16%	—
		Ride-hailing in an AV	−0.37%	0.18%	0.19%	—
		Using pooled AVs	0.18%	−0.01%	−0.09%	−0.09%
		Owning an AV vs. Ride-hailing in an AV	0.07%	0.07%	−0.05%	−0.08%
# of households: < 5 years old	Increase by 20%.	Owning an AV vs. Ride-hailing in an AV	−0.04%	−0.07%	0.01%	0.09%
# of households: 5–11 years old	Increase by 20%.	Owning an AV	−0.36%	0.20%	0.15%	—
		Ride-hailing in an AV	−0.28%	0.15%	0.12%	—
		Using pooled AVs	−0.08%	0.00%	0.04%	0.04%
		Owning an AV vs. Ride-hailing in an AV	−0.06%	−0.05%	0.04%	0.07%
# of households: 12–16 years old	Increase by 20%.	Owning an AV	−0.68%	0.39%	0.29%	—
		Ride-hailing in an AV	−0.53%	0.29%	0.24%	—
		Using pooled AVs	−0.15%	0.00%	0.07%	0.07%
		Owning an AV vs. Ride-hailing in an AV	−0.11%	−0.10%	0.08%	0.13%
Experience with public bus	Public bus is available to all individuals, and they use it.	Owning an AV	−5.21%	2.88%	2.33%	—
		Ride-hailing in an AV	−7.18%	3.67%	3.51%	—
		Using pooled AVs	−7.52%	−0.16%	3.72%	3.96%
		Owning an AV vs. Ride-hailing in an AV	−0.91%	−0.93%	0.66%	1.17%
Experience with light rail/tram/subway	Light rail/tram/subway is available to all individuals, and they use it.	Using pooled AVs	−2.69%	0.15%	1.33%	1.21%
Experience with commuter train	Commuter train is available to all individuals, and they use it.	Owning an AV	−1.56%	0.92%	0.64%	—
		Ride-hailing in an AV	−1.54%	0.87%	0.67%	—
		Using pooled AVs	−1.11%	0.05%	0.55%	0.51%
		Owning an AV vs. Ride-hailing in an AV	1.93%	1.71%	−1.47%	−2.17%
Experience with rental car	Rental car is available to all individuals, and they use it.	Owning an AV	2.41%	−1.48%	−0.82%	—
		Ride-hailing in an AV	2.20%	−1.32%	−0.87%	—
		Using pooled AVs	3.97%	−0.38%	−1.91%	−1.68%
		Owning an AV vs. Ride-hailing in an AV	0.44%	0.43%	−0.33%	−0.54%
Experience with ride-hailing	Ride-hailing is available to all individuals, and they use it.	Owning an AV	−8.22%	5.18%	3.04%	—
		Ride-hailing in an AV	−10.06%	5.84%	4.22%	—
		Using pooled AVs	−4.61%	0.35%	2.31%	1.94%
		Owning an AV vs. Ride-hailing in an AV	1.55%	1.40%	−1.18%	−1.77%
Experience with shared ride-hailing	Shared ride-hailing is available to all individuals, and they use it.	Using pooled AVs	−9.72%	−0.22%	4.91%	5.04%
		Owning an AV vs. Ride-hailing in an AV	2.02%	1.76%	−1.54%	−2.24%
Experience with carsharing	Carsharing is available to all individuals, and they use it.	Owning an AV	−6.37%	3.39%	2.98%	—
		Ride-hailing in an AV	−4.92%	2.53%	2.39%	—
		Using pooled AVs	−1.39%	0.03%	0.68%	0.68%
		Owning an AV vs. Ride-hailing in an AV	−0.97%	−0.97%	0.71%	1.23%
Experience with peer-to-peer car rental	Peer-to-peer car rental is available to all individuals, and they use it.	Owning an AV	−0.74%	0.43%	0.31%	—
		Ride-hailing in an AV	14.35%	−9.47%	−4.88%	—
		Using pooled AVs	13.55%	−2.26%	−6.37%	−4.93%
		Owning an AV vs. Ride-hailing in an AV	0.10%	0.09%	−0.08%	−0.12%
AV familiarity	All individuals have heard about AV and are very familiar.	Owning an AV	−16.72%	8.89%	7.83%	—
		Ride-hailing in an AV	−6.15%	3.74%	2.41%	—
		Using pooled AVs	−4.62%	0.09%	2.29%	2.24%
		Owning an AV vs. Ride-hailing in an AV	−5.03%	−6.09%	3.43%	7.69%
Housing	All individuals live in a building with ≥ 20 apartments.	Ride-hailing in an AV	−4.84%	2.52%	2.32%	—

(Continued)

Independent variable	Change in independent variable	Outcome variable	Probability of choice of category …			
			1	2	3	4
Income	All individuals have an annual household income ≥ \$150,000.	Owning an AV	−10.03%	5.80%	4.22%	—
		Ride-hailing in an AV	−5.01%	2.88%	2.13%	—
		Using pooled AVs	−0.75%	0.01%	0.37%	0.38%
		Owning an AV vs. Ride-hailing in an AV	−0.99%	−0.98%	0.73%	1.24%
Gender	All individuals are female/other.	Owning an AV	2.45%	−1.30%	−1.15%	—
		Ride-hailing in an AV	3.48%	−1.84%	−1.64%	—
		Using pooled AVs	2.23%	−0.05%	−1.08%	−1.10%
		Owning an AV vs. Ride-hailing in an AV	0.42%	0.42%	−0.31%	−0.54%
Employment	All individuals do not work for pay.	Owning an AV	5.88%	−3.31%	−2.58%	—
		Ride-hailing in an AV	1.21%	−0.60%	−0.60%	—
		Using pooled AVs	0.92%	0.07%	−0.44%	−0.55%
		Owning an AV vs. Ride-hailing in an AV	0.24%	0.25%	−0.18%	−0.32%
Education	All individuals have a graduate degree or higher.	Owning an AV	−0.41%	0.28%	0.12%	—
		Ride-hailing in an AV	−2.68%	1.63%	1.05%	—
		Using pooled AVs	−1.10%	0.16%	0.53%	0.42%
		Owning an AV vs. Ride-hailing in an AV	−0.09%	−0.08%	0.06%	0.10%
Drive frequency	All individuals have a driving license and drive every day.	Owning an AV	−0.17%	0.11%	0.06%	—
		Ride-hailing in an AV	−0.05%	0.04%	0.01%	—
Job type	All individuals (those who work) work from home.	Owning an AV	6.02%	−3.79%	−2.23%	—
Transit trips per week	Increase by 20%.	Owning an AV	−0.04%	0.00%	0.04%	—
Commute mode	All individuals drive alone to commute.	Owning an AV	−0.10%	0.06%	0.04%	—
		Ride-hailing in an AV	−0.08%	0.05%	0.03%	—
		Using pooled AVs	0.45%	0.10%	−0.20%	−0.35%
		Owning an AV vs. Ride-hailing in an AV	−0.13%	−0.10%	0.10%	0.14%
Commute days per week	Increase by 20%.	Owning an AV	0.60%	−0.30%	−0.30%	—
Ethnicity	All individuals are of Hispanic, Latino, or Spanish origin.	Owning an AV	−4.18%	2.26%	1.92%	—
Race	All individuals are White.	Owning an AV	1.58%	−0.86%	−0.72%	—
		Ride-hailing in an AV	1.93%	−0.86%	−1.07%	—
		Using pooled AVs	0.70%	0.05%	−0.35%	−0.40%
		Owning an AV vs. Ride-hailing in an AV	0.26%	0.27%	−0.19%	−0.34%

a direct impact. These are also considered in calculating the pseudo-elasticity effects.

The pseudo-elasticity values can be used to compare the impact of each independent variable on different forms of AV adoption. The percentage values in Table 5 can be interpreted as the increase or decrease in the aggregate probability of belonging to a level of an outcome variable when an independent variable is changed. For example, if the age of all individuals in the sample is assumed 65+ years old, the probability of belonging to the lowest (category 1) level of interest in owning an AV increases by 4.87% whereas the probability of belonging to the highest (category 3) level of interest in owning an AV decreases by 2.28% respectively.

4.3.2 Impact of the latent variables on AV adoption interests

It is not suitable to calculate the pseudo-elasticity effects of latent variables because there is no meaning in arbitrarily increasing the value of latent variables by a certain percentage. Instead, to investigate the impact of latent variables on different forms of AV adoption, we segment the sample into three equal terciles by the values of latent variables. As a result, segments having low, medium, and high pro-AV and pro-HV sentiments are obtained. Now, for each segment, the choice probabilities of all levels of outcome variables are obtained. However, for brevity, the choice probabilities of only two extreme levels (i.e., the lowest, and highest levels of interest) of outcome variables, based on the levels of each latent variable, are presented in Figs. 3 and 4. The impact of latent variables on each type of AV adoption can be observed in the figures. For example, the probability of choosing the highest level of interest in owning an AV is 24% for the segment with the high pro-AV sentiment but the same probability is 3% and 0%, respectively, for the segments with the medium and low pro-AV sentiment. It is to be noted that these sensitivities are based on the direct impacts of latent variables on outcome variables.

4.4 Discussion of results

Higher age group individuals (age > 35 years) show lower pro-AV and higher pro-HV sentiments compared to the younger aged (age 18–34 years). They also exhibit lower interest in owning an AV both in general and when compared to ride-hailing in an AV. Policy analysis shows that the probability of having the highest level of interest in owning an AV decreases by 2.28% when all sample is assumed 65+ years old (i.e., when 65.18% of the sample with age < 65 years are considered being 65+ years old). Thus, it can be concluded that the higher-aged individuals have a relatively lower interest in all forms of AVs, but when comparing owning an AV and ride-hailing in an AV, they relatively prefer the ride-hailing option on average. Overall, lower AV interests of higher-aged individuals could be explained by their low risk-taking

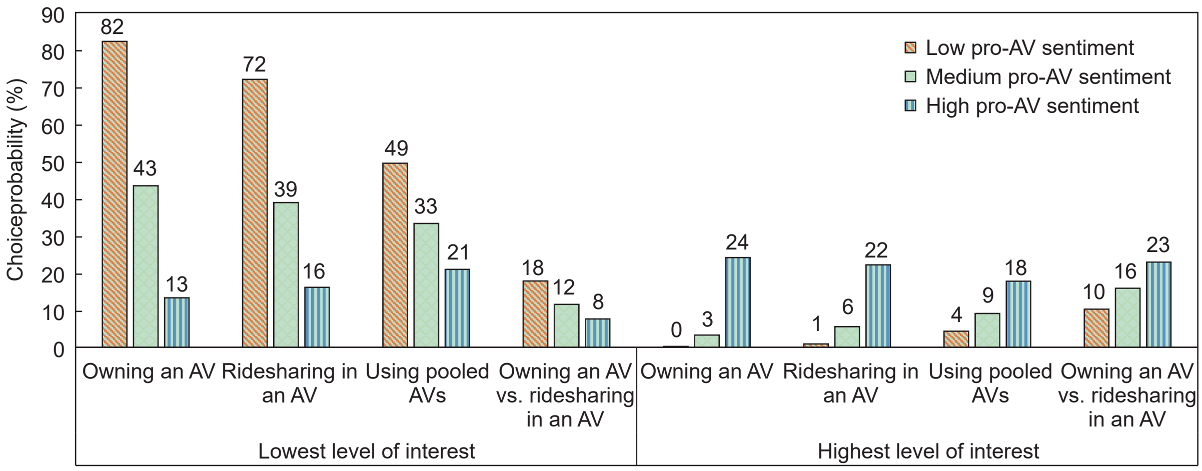

Fig. 3 Intention to adopt different forms of AVs for various levels of pro-AV sentiments.

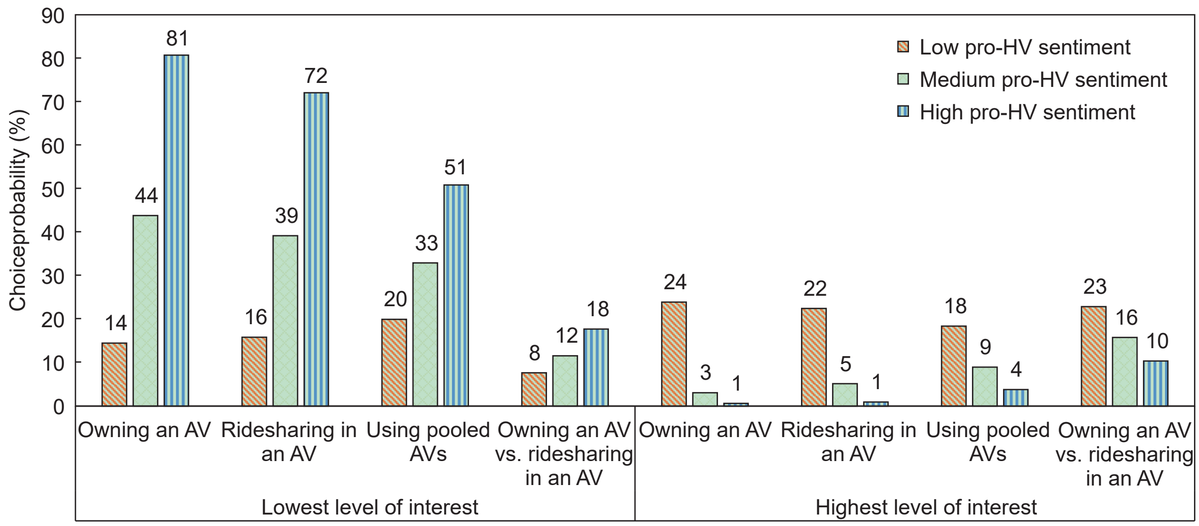

Fig. 4 Intention to adopt different forms of AVs for various levels of pro-HV sentiments.

behavior compared to younger-aged individuals as described in the socio-technological literature (Brell et al., 2019), as using an AV is considered a risky affair because of the uncertainty associated with the safety (Acharya and Humagain, 2022) and data privacy (Acharya and Mekker, 2022a). In addition, individuals of age 65+ years exhibit lower interest in using pooled AVs compared to other age groups. This could be related to the risks associated with the pooled vehicle services (e.g., compromised personal space, privacy, control, and convenience; Sanguinetti et al., 2019), and older-aged individuals having higher of these perceived risks in using pooled AVs. A similar finding is reported by Krueger et al. (2016).

Compared to males, females have higher pro-AV and lower pro-HV sentiments, and significantly lower interests in using ride-hailing and pooled AV options. Thus, when all the individuals in the sample are assumed female, the probabilities of having the highest levels of interest in owning, ride-hailing, and using pooled AVs decrease by 1.15%, 1.64%, and 1.10%, respectively. This result makes sense because females are relatively less tech-savvy (Kang et al., 2021) and have low-risk-taking behavior (Wang and Zhao, 2019) compared to males.

Individuals with a higher annual household income are found to have a higher pro-AV sentiment and a lower pro-HV sentiment. In addition, having a higher annual household income for an individual is directly related to a higher interest in owning an AV, but a lower interest in using pooled AVs. For policy implication, when all individuals in the sample are assumed to have annual household income ≥ \$150,000, the probability of having the highest interest in owning an AV increases by 4.22%. This result indicates that low-income individuals worry about the higher costs of owning AVs compared to current HVs as described in Asmussen et al. (2020), but they still prefer the low-cost AV option, i.e., pooled AVs.

Pro-AV sentiment increases with an increase in the number of children of the age group 5–16 years in the household. There is an insignificant direct impact of the number of households on all forms of AVs, but a slightly higher interest in owning an AV is observed for the individuals with a higher number of children (age < 5 years) in the household when compared with ride-hailing interest. Policy analyses show that households with a higher number of children (age ≤ 16 years) tend to have a slightly higher adoption interest in all forms of AVs. These results reflect that AVs offer a way to improve the travel experience of families with children as automated driving can relieve the stress of manual driving with children (because of dual responsibilities in HV driving—driving the vehicle and taking care of children in-vehicle at the same time) by freeing up the time to take care of children in-vehicle.

Employment has a significant impact on AV ownership interest. Those who do not work for pay have lower interest, and thus, when all the individuals in the sample are assumed not to work for pay, the probability of having the highest level of interest in owning an AV decreases by 2.58%. This is explained by a lower mobility need of the individuals who do not work for pay.

In terms of ethnicity and race, Hispanic/Latino/Spanish origin individuals have a higher interest in owning AVs. Asians have higher pro-AV, lower pro-HV sentiments, and higher interest in ride-hailing in an AV, whereas Black/African Americans have lower interest in ride-hailing in an AV. In line with previous studies (e.g., Esterwood et al., 2021), this finding supports the fact that there exist differences in attitudes and interests in different forms of AVs based on ethnicity and race.

Travel behavior literature agrees that an individual's attitude/perception towards a travel mode is influenced by his/her experience with that travel mode and other travel modes (De Vos et al., 2021). In this study, we also find the significant impacts of the experiences of individuals with different travel modes on their sentiments related to AVs and HVs, and on adoption interests for different forms of AVs. Some key results from policy analysis are presented here. The probability of having the highest interest in ride-hailing in an AV and using pooled AV increase by 3.51% and 3.96%, respectively, when all sample is assumed to have experience with the public bus. The probabilities of having the highest level of interest in owning an AV and ride-hailing in an AV increase by 3.04% and 4.22%, respectively, when all samples are assumed to have experience with current ride-hailing services. Similarly, when all samples are assumed to have experience with current shared ride-hailing services, the probability of having the highest level of interest in using pooled AVs increases by 5.04%. The experience with carsharing influences the interest in owning an AV the most, with the increase in the probability of having the highest interest in owning an AV by 2.98% when all sample is assumed experienced. In terms of experience with peer-to-peer car rental, when all sample is assumed experienced, the probabilities of having the highest interest in ride-hailing and pooled AVs decrease by 4.88% and 4.93%, respectively. Using carpool services as a daily commute mode is associated with a higher interest in using pooled AV services. Similarly, higher interest in using pooled AVs and lower interest in owning AVs instead of ride-hailing are observed for those individuals who walk/bike for daily commutes. Overall, individuals having experience with green travel modes (Nazari et al., 2018) exhibit positive sentiments towards using AVs as on-demand services whereas the experience with some tech-savvy modes (e.g., carsharing) is associated with a higher interest in owning private AVs.

The number of commute days per week has a direct negative impact on AV owning interest. When all individuals are assumed to have their number of commute days per week by 20%, the probability of having the highest interest in owning AVs decreases by 0.30%. This is also explained by the fact that vehicle ownership interest increases with an increase in mobility needs.

After the global COVID-19 pandemic, the concept of working from home and its impact on travel behavior is of keen interest. Though working from home doesn't have an impact on pro-AV and pro-HV sentiments, it has a direct negative impact on AV-owning interest. When all individuals in the sample are assumed to work from home, the probability of having the highest level of AV-owning interest decreases by 2.23%. This result aids the finding of past post-COVID studies (e.g., Rafiq et al., 2022) that working from home reduces private vehicle ownership, commute travel, and overall vehicle miles traveled, and the same can be expected during the AV era too.

The only built environment characteristic considered in the study (i.e., type of housing) is significantly associated with AV adoption interests. On average, individuals living in buildings with ≥ 20 apartments show a higher interest in using AVs as ride-hailing services. When all individuals in the sample are assumed to be living in buildings with ≥ 20 apartments, the overall probability of having the highest level of interest in ride-hailing AVs increases by 2.32%. This result is supported by the mode choice literature that the feasibility and/or public interest in shared transport services (including AV ride-hailing) increase with an increase in population density (Rahman and Sciara, 2022), as it is highly likely that the buildings with ≥ 20 apartments belong to dense and compact neighborhoods.

Out of the seven regions classified in the study, individuals from the rest of the state have higher pro-AV sentiments whereas individuals from the San Francisco area have lower pro-HV sentiments, and these individuals (from both regions) show a higher interest in ride-hailing in an AV. Similar to Jiang et al. (2020), this result provides evidence of the spatial differences in attitudes and behavioral intentions to use different forms of AVs.

Higher AV familiarity is associated with higher pro-AV and lower pro-HV sentiments respectively, and higher interest in all forms of AV, in general. When all individuals in the sample are assumed very familiar with AVs (i.e., 42.65% of the sample with no AV familiarity and 43.04% of the sample with somewhat AV familiarity are considered having high AV familiarity), the probability of having the highest interests in owning, ride-hailing, and using pooled AVs increase by 7.83%, 2.41%, and 2.24%, respectively, and the probability of choosing to own an AV over ride-hailing option increases by 7.69%. This result indicates that increased familiarity or interaction with AVs helps to develop positive attitudes towards AVs, similar to that identified by Acharya and Mekker (2022b) in the case of connected vehicles. Thus, one area AV stakeholders should work on is increasing public familiarity with AVs. This could be achieved by educating the public about the benefits of AVs (increased safety, reduced driving stress, possibility to work and leisure in-vehicle, etc.), advertising the available autonomous features (lane-keep assistance, adaptive cruise control, parking assistance, emergency braking, etc.), developing new marketing strategies to familiarize the public with autonomous features, etc. Interestingly, the impact of AV familiarity is positively higher towards owning compared to the ride-hailing option. This shows that the current AV familiarity is mostly related to owning AVs compared to ride-hailing, and thus we suggest future public outreach efforts focus more on shared AV services along with private AVs.

Both latent variables—pro-AV and pro-HV sentiments—exhibit significant associations with all outcome variables. The pro-AV sentiment is positively related to all forms of AV adoption, whereas the pro-HV sentiment is negatively related. The policy analysis provides the sensitivities of the impacts of latent variables on the outcome variables. The probability of having the highest level of interest in owning an AV is 24% for the segment with the high pro-AV sentiment but the same probability is 3% and 0%, respectively, for the segments with the medium and low pro-AV sentiment. Opposingly, pro-HV sentiment has the opposite impact. The probability of choosing the highest level of interest in owning an AV is 24% for the segment with the low pro-HV sentiment but the same probability is 3% and 1%, respectively, for the segments with medium and high pro-HV sentiments. The results show that the impact of both latent variables on the outcome variables is in the order of owning an AV, ride-hailing in an AV, and using pooled AVs, with the highest impact on interest in owning an AV. These differences in sensitivities of the impacts of pro-AV and pro-HV sentiments on different forms of AV could be related to people considering ride-hailing and pooled AV services similar to currently available on-demand services, but private AVs (owning option) significantly different from the currently available HVs. Overall, it can be concluded that the pro-AV sentiment increases the interest in all forms of AVs, but the pro-HV sentiment reduces the interest in all forms of AVs.

A higher impact of pro-HV sentiment on all forms of AV adoption indicates that pro-HV sentiment is a major barrier to AV adoption. Here, the pro-HV sentiment is related to the joy of manual driving and no need for automation. This brings the stakeholders' attention to developing hybrid AVs—having both self and manual driving modes—such that the AVs can be driven in manual driving mode and the joy of driving can be preserved in the AV era too. Acharya et al. (2023) have also made similar recommendation based on the analysis of driving satisfaction of long-distance travelers with respect to several advanced vehicle features. This could be a potential strategy for attracting pro-HV consumers towards owning private AVs and using AVs' (pooled) ride-hailing options.

5 Conclusions

5.1 Concluding remarks

With the necessity to understand the public interest in adopting AVs as private vehicles and on-demand services, we jointly model the interests in owning an AV, ride-hailing in an AV, using pooled AVs, and owning an AV vs. ride-hailing in an AV by considering the numerous socio-demographics, travel behavior-related, and attitudinal variables using a combination of structural equation modeling and multivariate ordered probit modeling frameworks. The data used in the study are drawn from the CVS conducted by the California Energy Commission in 2019. The estimation results show that several individual socio-demographics (age, gender, employment, ethnicity, race), household socio-demographics (income, household size), travel-related characteristics (experience with different travel modes, usual commute mode, commute days per week), built-environment characteristics (housing type), and some other characteristics (region of residence, AV familiarity) impact the different forms of AV adoption interests either directly or indirectly through the latent variables. Both latent variables (pro-AV and pro-HV sentiments) impact all forms of AV adoption but in opposite directions: pro-AV sentiment is positively related to all forms of AV adoption, but pro-HV sentiment has the opposite relationship.

In addition, we test several policy implications in our model estimates. First, we calculate the pseudo-elasticity effects where the exogenous variables are changed to see the impacts on the outcome variables. The results show the varying impacts of different exogenous variables on different outcome variables. In general, familiarity with AVs has the greatest impact on all forms of AV adoption, followed by travel characteristics and individual/household demographics. Second, we visualize the sensitivities of the impacts of latent variables on the outcome variables by segmenting the sample into three terciles based on the values of the latent variables. When comparing the impacts of latent variables on the AV adoption options, the overall sensitivities of pro-AV and pro-HV sentiments are almost equal. However, these sentiments are found to have the greatest impact on interest in owning an AV compared to other forms of AV adoption (ride-hailing and pooled AVs). We interpret these differences because of the public considering private AVs significantly different from current HVs but ride-hailing and pooled AV options somewhat similar to currently available on-demand services.

Overall, the study identifies the critical determinants of adoption interest in different forms of AVs. These findings could be used not only to understand the anticipated changes in travel behavior when AVs come to the real roads and to formulate plans to better accommodate the changes in travel patterns, but also to shape future travel patterns. Instead of owning private AVs, using shared AVs (ride-hailing or pooled) would be more sustainable because of the overall environmental and mobility benefits (Silva et al., 2022). The differences in adoption interest in shared vs. private AVs identified in this study could be utilized to attract more individuals to shared AV services as a path to make the transportation system sustainable. For example, improving the flexibility and reliability of shared AV services could help attract more high-income individuals, whereas lowering the cost could help attract more low-income individuals.

5.2 Study strengths and limitations

This study is more robust than existing past studies, mostly in three areas. First, the consideration of all forms of AV adoption (owning private AVs, ride-hailing in AVs, and using pooled AV services) is rarely made in past studies. When AVs come to the market, they are highly likely to come as on-demand services (ride-hailing and pooled) along with private vehicles. Thus, with this potential, the modeling of public interest in all forms of AVs is superior to considering one form only. In addition to this, we also directly compare the interests in owning an AV vs. ride-hailing in an AV such that insights behind the preference of one AV option over another are made. Second, we consider a wide range of exogenous variables: individual demographics, household demographics, travel-related characteristics, and built-environmental characteristics, in addition to attitudinal variables: pro-AV and pro-HV sentiments. Considering this wide range of exogenous variables allows us to examine the impact of different variables on AV adoption interests when the relationship is controlled by other factors. In addition, individual differences in the perception of AV adoption interest might exist regardless of the differences in individual and household demographics, travel-related characteristics, and built environment characteristics, and considering stochastic attitudinal variables somehow captures such differences, as in this study. Third, unlike past studies, we conduct several policy analyses to quantify the impact of exogenous and latent variables on the outcome variables. These results are helpful to formulate the policy implications. For example, if all individuals are made very familiar with AVs, the overall public interest in owning private AVs increases by more than 7%.

We identify three shortcomings in this study that could be addressed through additional research. First, the study is limited considering two latent variables relating to attitudes toward automated and human driving only, however, some other attitudinal variables such as technology savviness, travel attitudes, environmental concerns, etc. might also potentially impact the adoption of different forms of AVs, as found in several past studies (e.g., Haboucha et al., 2017; Nazari et al., 2018). Second, the available dataset allows us to consider only one built environment characteristic, i.e., housing type. Considering other built environment characteristics, such as population density, type of neighborhood, land use type, etc. broadens our understanding of relationships between AV adoption interests and the built environment. Third, more realistic estimates could be obtained by replacing the two-stage modeling strategy adopted in this study with a simultaneous estimation method proposed by Bhat (2015) though the computational burden increases.

Appendix

Table A1 Results of exploratory factor analysis (EFA) of attitudinal variables related to automated and manual driving

Variable	Loading	
	Factor 1	Factor 2
Enjoy traveling more in an AV	0.679	−0.242
Accept longer travel in an AV	0.593	−0.081
Work in an AV	0.797	0.112
Escort child in an AV	0.691	−0.036
Travel in an AV even when fatigued	0.691	0.034
Miss joy of driving in the AV era	0.054	0.658
No need for automation	−0.085	0.749
Proportional variance	37.40%	15.3%

Note: Loadings > 0.4 are bold; factors 1 and 2 are named "Pro-AV sentiment" and "Pro-HV sentiment" respectively. Estimation is done with minimum residual (MR) factoring with oblimin factoring using the "psych" package (Revelle, 2017) in R (R Core Team, 2022).

Replication and data sharing

The replication package for this study is available for download at https://doi.org/10.26599/ETSD.2023.9190016. The package provides information on how to clean the raw datasets and used them for several analyses presented in the paper. Additional details are provided in the explanatory file included as part of the replication package.

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Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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