Transportation Research Part A 168 (2023) 103535

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Deciphering the factors associated with adoption of alternative fuel vehicles in California: An investigation of latent attitudes, socio-demographics, and neighborhood effects

Xiatian Iogansen [a,*], Kailai Wang [b], David Bunch [c], Grant Matson [a], Giovanni Circella [a,d,e]

[a] Institute of Transportation Studies, University of California, Davis, 1715 Tilia Street, Davis, CA 95616, United States
[b] Department of Construction Management, University of Houston, 4730 Calhoun Road #332, Houston, TX 77004, United States
[c] Graduate School of Management, University of California, Davis, Gallagher Hall, Room 3402, Davis, CA 95616, United States
[d] Department of Geography, Ghent University, S8 Campus Sterre, Krijgslaan 281, 9000 Ghent, Belgium
[e] School of Civil and Environmental Engineering, Georgia Institute of Technology, 790 Atlantic Drive, Atlanta, GA 30332, United States

A R T I C L E I N F O

Keywords:
Vehicle fuel type choice
Alternative fuel vehicle (AFV)
Integrated choice and latent variable (ICLV) model
Adoption behavior modeling
California

A B S T R A C T

Promoting the use of alternative fuel vehicles (AFVs) has become a long-term transportation strategy in California, which can bring a broad range of social, economic, and environmental benefits. Based on a sample of 3260 California residents from the 2018 California Panel Survey, this study explores the impacts of latent attitudes, socio-demographic characteristics, and neighborhood effects on consumers' *current vehicle fuel type choice* and *their interest in purchasing or leasing an AFV in the future*. One joint integrated choice and latent variable (ICLV) model is estimated to understand the taste heterogeneity within different population segments. The results suggest that latent attitudes towards *environment*, *new technologies*, *car-utilitarianism,* and *residential location preference* play critical roles in individuals' adopting new vehicle technologies. A range of socio-demographics, including age, race, gender, student status, education level, income level, household size, housing tenure, housing type and residential parking also make effects. Exposure to BEVs in both residential location and worksite has positive influence on AFV adoption, although public EV charging stations were not found to be essential factors since our respondents may mainly rely on home chargers. Moreover, the study suggests that individual's current user experience with AFVs has positive effect on their future interest in AFV. Overall, we predict the maximum market penetration of AFVs could be 41% of adult population. The findings offer detailed guidance on crafting California's transport policy to promote AFV, regarding the heterogeneity of the population's preferences and attitudes.

Abbreviations: ACS, American Community Survey; AFV, alternative fuel vehicle; ASC, alternative specific constant; BEV, battery electric vehicle; DCM, discrete choice models; DOE, Department of Energy; EFA, exploratory factor analysis; EVSE, electric vehicle supply equipment; FFV, flexible fuel vehicle; FCEV, fuel cell electric vehicle; GHG, greenhouse gas; HCM, hybrid choice model; HEV, hybrid electric vehicle; ICEV, internal combustion engine vehicle; ICLV, integrated choice & latent variable; MTC, Metropolitan Transportation Commission; NGV, natural gas vehicle; PEV, plug-in electric vehicles; PHEV, plug-in hybrid electric vehicle; SACOG, Sacramento Area Council of Governments; SANDAG, San Diego Association of Governments; SCAG, Southern California Council of Governments; SDB, social desirability bias; US, United States; ZEV, zero-emission vehicle.

* Corresponding author.
E-mail addresses: xtwu@ucdavis.edu (X. Iogansen), kwang43@central.uh.edu (K. Wang), dsbunch@ucdavis.edu (D. Bunch), gamatson@ucdavis.edu (G. Matson), gcircella@ucdavis.edu (G. Circella).

https://doi.org/10.1016/j.tra.2022.10.012
Received 20 August 2021; Received in revised form 22 April 2022; Accepted 23 October 2022
Available online 6 January 2023
0965-8564/

1. Introduction

Encouraging the adoption of alternative fuel vehicles (AFVs) has emerged as a major ongoing policy goal in California's efforts to control pollutants and greenhouse gas (GHG) emissions, and more broadly mitigate adverse environmental impacts related to the reliance on petroleum motor fuels. From a consumer perspective, AFVs reduce fuel costs and can change the economic structure of mobility choices at the household level (e.g., Ogden et al., 2004). For our purposes, vehicles with the following four alternative fuel powertrains will be denoted AFVs.[1]

a) **Plug-in hybrid electric vehicles (PHEVs)** have a gas and electric propulsion system that allows the car to run on electricity alone within a limited range, usually between 6 and 40 miles.
b) **Battery electric vehicles (BEVs)** run solely on battery power with a longer range than PHEVs, commonly between 80 and 100 miles with a few models more than 250 miles. PHEVs and BEVs are together referred as **plug-in electric vehicles (PEVs)**.
c) **Hydrogen fuel cell electric vehicles (FCEVs)** have on-board fuel cells that run on compressed hydrogen, with the advantage of zero tail-pipe emissions and high efficiency.
d) **Natural gas vehicles (NGVs)** run on compressed or liquefied natural gas and have cleaner emissions.

Established in January 2018, the California Zero-Emission Vehicle (ZEV) Action Plan set an ambitious target of 1.5 million ZEVs (a mix of PHEVs, BEVs and FCEVs) on the road by 2025, on a path to 5 million by 2030. California has established mandates that require auto manufacturers to make available specific numbers of these vehicles to support achieving these targets (California Air Resources Board, 2020). While California is far ahead of most penetration curves when compared to other locations, PEVs accounted for only 7.8 % of California's new vehicle sales in 2018 (Evadoption, 2022). Nevertheless, as of February 2022, more that 1million ZEVs were on the road in California. While this increase is encouraging, many challenges still lie ahead.

Policymakers have advocated the use of AFVs for decades, going back to California's original exploration of a 2 % EV sales mandate in the late 1990′s (Collantes and Sperling, 2008). It was always well understood that a transition from incumbent conventional fuel vehicles to AFVs would not happen spontaneously and would rely heavily on policy interventions to support the innovation diffusion process during early stages of market development. It was also well understood initial introduction of AFVs would be hampered by high production costs and limitations on, e.g., the availability of refueling/recharging infrastructure and driving range. On the other hand, even at introduction AFVs would have advantages in, e.g., fuel operating cost, and potential convenience from home charging. Moreover, new technologies with improved environmental benefits could be attractive to a segment of early adopters that would help initiate the dynamic process of market development. An important aspect of these dynamics is the reduction in cost and improvement of technologies and features from learning effects that occur as a function of cumulative production, so that the market evolves to offer products acceptable to mainstream consumers.

For policymakers to design and implement policies to support this market formation process requires a detailed understanding of what factors would influence individuals' adoption and usage of AFVs over the course of this process. This gave rise to many studies across an array of relevant academic disciplines. The vast majority of studies were conducted during a period when there were essentially no AFVs in the marketplace, requiring highly exploratory research approaches and methodologies that employ hypothetical vehicle descriptions (e.g., discrete choice experiments). Even now, some 12 years after the introduction of PEVs in 2010, the general population in most markets has very limited awareness and knowledge of PEVs, so there continues to be additional studies employing similar approaches. At the same time, the number of PEV offerings has increased in recent years, and a growing segment of early adopters has been purchasing and using them. These consumers have been targeted and extensively studied to understand in detail which factors contributed to their adoption decision (including the role of existing policy-related incentives), and how this segment differs from the general population. While this has been going on, researchers' interests have expanded to include other mobility options (e.g., ride-hailing/sharing, car sharing, bike sharing, e-bikes and e-scooters) including the possibility of self-driving (autonomous) vehicles.

Within this context, our study uses survey data from a snapshot in time (2018) of 3260 respondents from California's general population, which corresponds to a vehicle market much further down the AFV adoption curve than most other markets in the US. The survey is not a focused vehicle-specific survey with, e.g., discrete choice experiments incorporating detailed vehicle attributes. Rather, it is a general-purpose transportation/mobility survey covering a wide range of issues, but with detailed questions on attitudes, lifestyle, activities, and socio-demographics. The vehicle-related questions are limited to (i) information about the vehicle they currently use, and (ii) a question about their interest in ever purchasing vehicles that run on alternative fuels in the future. There is no prior "educational" information giving definitions of terms, so their responses are based exclusively on whatever awareness, knowledge, and beliefs about AFVs that they held at the time.

When considering an individual's responses to the current adoption of and future interest in AFVs, there is little doubt that a standard statistical analysis will suggest that the two responses are interrelated (i.e., correlated). Therefore, the goal of our analysis is twofold. The first is to identify the details of how specific factors affect consumers' *current vehicle fuel type choice* and *interest in purchasing or leasing a BEV/Hydrogen FCEV in the future*, respectively. Specifically, theory suggests that some factors may have similar effects on both choices, while others may differ in important ways. Adequately addressing these factors supports the second goal: To

[1] **Flexible fuel vehicles (FFVs)** run on a mixture of gas and ethanol. They have frequently been denoted AFVs but given that most FFVs primarily use gasoline, we view them as internal combustion engine vehicles for this study.

ascertain the potential effect of an individual's experience with their current vehicle choice on their interest in a future BEV/Hydrogen FCEV. Our approach is to estimate a joint integrated choice & latent variable (ICLV) model to identify the source of heterogeneous AFV preferences within the population, focusing on latent attitudes, socio-demographics, and residential characteristics. In addition, we augment the survey data with variables from external source to investigate potential neighborhood and infrastructure effects.

The contribution of this study is threefold. First, we incorporate information on attitudes to capture what would otherwise be unobservable. The estimated latent factors explicitly account for the taste heterogeneity in the process of adopting AFV. Therefore, policymakers and advocates for new vehicle technologies could effectively respond to different population segments. Second, California has a larger number of AFV adopters, higher market share, and better infrastructure supplies than other states (California Air Resources Board, 2020; Shaheen et al., 2020), which provides an opportunity for a detailed assessment. The assessment results will offer valuable insights to other markets that are relatively lower in the penetration curves. Third, we compare the correlates of consumers' current choice and their future intention, revealing the importance of current user experiences on AFV adoptions.

The remainder of this paper is organized as follows. Section 2 reviews relevant literature. Section 3, 4 and 5 describe the dataset, provide preliminary analyses, and discuss mathematical details of our model framework. The model results are presented in Section 6. We conclude our paper with discussions and policy recommendations in Section 7.

2. Literature review

2.1. Factors influencing the adoption of AFVs

As noted in the introduction, there is a substantial literature investigating factors that could potentially influence the adoption of AFVs, using a wide range of methodologies. Because this is essentially a problem in understanding consumer behavior, a variety of social science theories and approaches are applicable. At one level, an AFV is just one more instance of a "vehicle", a product category where the core benefit is providing personal mobility over more-than-short distances. The technological implementation of such an offering may be evaluated by consumers based on a number of vehicle characteristics that have some impacts on overall preferences such as purchase price and operating cost (Breetz and Salon, 2018; Daziano and Achtnicht, 2012; Giacomo and Noussan, 2021; Helveston et al., 2015; Musti and Kockelman, 2011; Potoglou and Kanaroglou, 2007; She et al., 2017; Tanaka et al., 2014), driving range (Danielis et al., 2018; Liu et al., 2021), and seating/cargo capacity.

Formally, when a consumer makes a vehicle purchase decision, they select from a set of competing alternatives, so discrete choice modeling has been a widely used methodology for obtaining quantitative measures of consumer preferences for vehicle characteristics. These types of applications typically include the identification of how preferences might vary as a function of consumer characteristics such as household income, age, gender, household size, educational level(Sovacool, 2009), so-called "observable heterogeneous preferences". Because until recently AFVs have not existed in the marketplace, discrete choice experiments using hypothetical vehicle descriptions have been employed. Although this approach has applications for existing products, it is especially relevant when estimating potential demand for new-to-the-world products with features or characteristics that are notably different from the status quo. A widely cited early application for California is by Bunch et al. (1993), and many similar studies have subsequently appeared addressing many different markets (Al-Alawi and Bradley, 2013; Axsen et al., 2010; Jensen et al., 2014; Lee et al., 2019).

Beyond such issues as consumer preferences and demographic segmentation, there are other features of transitioning from conventional fuel vehicles to AFVs that are critically important. AFVs adoption is frequently viewed through the len of diffusion of innovation theory (Lee et al., 2019). However, there are some features that are notably challenging. First, the primary motivation for a transition to AFVs is the need for reduced emissions, which is a public good. Second, the services provided by AFVs are a very close substitute for those offered by an entrenched incumbent with cost advantages (i.e., conventional vehicles). These features mean that such a diffusion of innovation is highly unlikely to occur naturally: policy interventions, such as increasing gasoline taxes, purchase price subsidies, and tax exemptions are required (Al-Alawi and Bradley, 2013; Sierzchula et al., 2014; Soto et al., 2014, 2018, 2021). Third, purchases in this product category require a relatively infrequent expenditure on a durable good that represents a relatively large portion of most household budgets (in contrast to, e.g., microwave ovens, smartphones). Finally, transitioning to AFVs is not simply a matter of switching vehicles. How these vehicles can be used is also determined by an additional non-vehicle feature: refueling infrastructure, including availability, fuel type, location, and price, which is essential to the successful adoption of AFVs (Al-Alawi and Bradley, 2013; Egbue and Long, 2012).

Aside from these factors, several other diffusion-related concepts are highly relevant. Initially introduced versions of a new product will be purchased only by a small group of early adopters who are highly motivated by an interest in new technology and unconcerned with the "risk" of trying a new and unproven product. Over time, other segments of the population gain awareness and exposure to the new product through, e.g., *social interaction* with those from segments who tend to adopt earlier (Jansson et al., 2017; Manca et al., 2020). In contrast to choices from among existing products with much higher familiarity, choosing to consider and evaluate new products relies more heavily on cognitive processes involving *perceptions* and *attitudes* (Wang et al., 2021), so-called "unobservable heterogeneous preferences".

Another aspect of market formation dynamics is that the products themselves go through cycles in which features are improved, manufacturing costs (and therefore prices) go down due to learning effects, and the number of offerings increases, along with differentiation that satisfies a wider range of consumer preferences.

All these different factors have been widely researched in the literature, with most results being obtained using methodologies that (by necessity) do not require direct, real-world experience with AFVs. In considering preferences for vehicle attributes, the dynamic aspects of AFV introduction ensure that there will be obstacles early in the process (high prices, limits on features, and limited

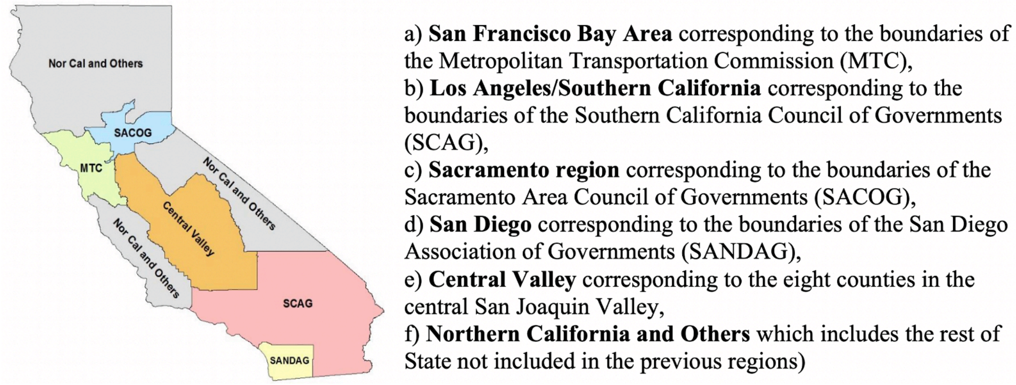

Fig. 1. Six regions of California included in this study.

offerings). Moreover, the influence of social and psychological factors ensures that there will be substantial unobserved heterogeneity in preferences. All these factors are also highly relevant to policy makers, who must take actions to support a dynamic market formation process that would not occur otherwise and must do so making the most efficient use of limited resources.

As noted in the introduction, the study presented here focuses on a snapshot of the California market in 2018, a time in which a reasonably sized survey of the general population will include a measurable (albeit relatively small) subset of individuals with experience using PEVs. More generally, this survey represents a snapshot of a developing AFV market that is notably further along than most other markets. The survey is a general transportation survey and not focused on vehicles per se, i.e., there are essentially no measurements related to vehicle attributes. The focus is on socio-demographics, attitudes and lifestyle preferences, and current and anticipated behavior in relation to AFVs.

2.2. Modeling approaches for studying the adoption of AFVs

There is evidence of significant progress in modeling the adoption of AFVs. Earlier studies used cluster analysis to emphasize the importance of attitudes in behavioral decisions (Anable, 2005; Dallen, 2007; Jansson et al., 2009). Galván et al. (2016) employed a series of discrete choice models, namely, multinomial logit model, nested logit model, mixed logit model, and mixed logit model with a panel effect term, to analyze the factors that influence the demand for alternatively fueled buses in Colombia. To provide more realistic modeling results, Bolduc et al. (2008) adopted a hybrid choice modeling approach to understand the adoption of vehicle technologies. This approach incorporates attitudes and perceptions as latent variables. In line with this, Daziano and Bolduc (2013) introduced Bayesian methods to build the statistical model.

Hybrid choice modeling is a commonly used method for analyzing the adoption of new vehicle technologies. At the early stage of electric vehicle penetration, Glerum et al. (2014) estimated a hybrid choice model that accounts for attitudes in the decision-making process to forecast the future demand. Using the same approach, Jensen et al. (2013) analyzed the changes in individual attitudes and preferences after experiencing an EV in their daily life. They found that significant changes happened to the priorities on driving range, top speed, fuel cost, battery life, and charging locations. More importantly, they found that environmental concern positively affects the preference for electric vehicles. Loss aversion (Mabit et al., 2015) and latent habitual effect (Valeri and Cherchi, 2016) were also found to affect the adoption of AFV significantly. Kim et al. (2014)) applied an expanded hybrid choice by simultaneously estimating the effects of social influences and latent attitudes on the intention to purchase electric vehicles. Overall, the impact of social networks on purchasing behavior was not strong; however, it depends on the types of social networks (i.e., peers, friends, family, colleagues) and the level of market shares in these types of social networks. Some studies have also employed general structural equation models to study the adoption of AFV (Morton et al., 2016; Rezvani et al., 2018).

In our study, we employ a version of hybrid choice/ICLV models that share many similarities with previous studies (Bansal et al., 2021; Ghasri et al., 2019; Jung et al., 2021; Qian et al., 2019). For example, the AFV literature has evolved so that attitudes related to environmentalism and interest in technology are frequently included in modeling frameworks and found to be related to AFV adoption. In most cases, these models are developed around discrete choice experiments for vehicle attributes. In our case, we limit consideration to whether respondents currently use a PHEV or BEV (in contrast to an internal combustion engine vehicle, or ICEV), and also on their stated likelihood to consider an AFV for a future purpose. An important feature of our analysis is that it estimates structural relationships to disentangle what would otherwise be highly correlated effects.

3. Data

3.1. 2018 California panel survey data

The dataset used in this study was collected in 2018, as the second wave of data collection of a large longitudinal research project that investigates the impacts of emerging transportation technology and new mobility services on people's travel behavior and vehicle

Table 1
Variables for weighting and gaps between final weights and target distribution.

A	B	C	D	E	F	G (=E-C)	H	I	J (=H-C)
		Population		Survey		Original Gaps	Final Weights		**Final Gaps**
		Perc	Freq	Perc	Freq	Perc	Perc	Freq	**Perc**
Region	Central Valley	10.0%	375	11.0%	414	1.0%	9.7%	367	**-0.21%**
	MTC	20.1%	758	25.4%	955	5.2%	21.2%	800	**1.10%**
	NorCal and Others	7.1%	269	12.8%	483	5.7%	6.5%	245	**-0.63%**
	SACOG	6.3%	236	10.4%	392	4.1%	6.2%	235	**-0.03%**
	SANDAG	8.5%	322	13.2%	499	4.7%	8.6%	322	**0.01%**
	SCAG	48.0%	1807	26.8%	1009	-21.2%	47.7%	1797	**-0.24%**
Neighborhood Type	Rural	29.3%	1104	23.2%	1181	-6.1%	27.1%	1023	**-2.17%**
	Suburban	47.1%	1773	45.4%	1711	-1.7%	46.7%	1759	**-0.39%**
	Urban	23.6%	889	31.4%	875	7.7%	26.2%	986	**2.56%**
Age	18-34	32.4%	1222	21.6%	813	-10.9%	31.9%	1203	**-0.52%**
	35-54	34.4%	1296	36.0%	1358	1.6%	34.5%	1300	**0.10%**
	55 and above	33.2%	1249	42.4%	1596	9.2%	33.6%	1265	**0.42%**
Gender	Male	49.1%	1849	53.3%	2006	4.2%	49.3%	1858	**0.23%**
	Female	50.6%	1905	46.5%	1753	-4.0%	50.3%	1897	**-0.21%**
	Other	0.4%	13	0.2%	8	-0.1%	0.3%	12	**-0.02%**
Race and ethnicity	Asian, Hispanic	0.2%	8	0.4%	16	0.2%	0.2%	8	**0.01%**
	Asian, Not-Hispanic	15.4%	580	11.1%	420	-4.3%	15.3%	578	**-0.07%**
	Other, Not-Hispanic	8.6%	324	7.2%	270	-1.4%	8.6%	324	**0.01%**
	White, Not-Hispanic	41.1%	1547	60.8%	2290	19.7%	41.9%	1580	**0.88%**
	White and other, Hispanic	34.7%	1308	20.5%	771	-14.3%	33.9%	1277	**-0.83%**
Household Annual Income	Below $50,000	31.3%	1180	31.7%	1195	0.4%	31.3%	1180	**-0.02%**
	$50,000 to $99,999	28.6%	1077	32.2%	1213	3.6%	28.8%	1084	**0.21%**
	$100,000 and above	40.1%	1510	36.1%	1359	-4.0%	39.9%	1503	**-0.18%**
Presence of child(re	Married with child(ren)	38.4%	1445	31.4%	1183	-7.0%	37.8%	1424	**-0.56%**
	Married without child(ren)	61.6%	2322	68.6%	2584	7.0%	62.2%	2343	**0.56%**
	Single	22.9%	863	34.1%	1283	11.1%	23.4%	880	**0.44%**
Student and work sta	Student only	3.2%	120	2.2%	82	-1.0%	3.2%	119	**0.00%**
	Student and worker	8.5%	321	8.4%	317	-0.1%	8.6%	323	**0.05%**
	Worker only	65.4%	2463	55.3%	2085	-10.0%	64.9%	2445	**-0.49%**

ownership within the State of California (Circella et al., 2019). The data collection was completed through a mixed sampling method as follows. In the end, these three channels generated 4071 complete responses:

1. A paper survey was mailed out to a stratified random sample of 30,000 California residents, by adjusting the sampling rates to obtain sizable numbers of respondents in all six geographic regions (as Fig. 1 depicts).
2. A sample of 2000 Californians was recruited through an online opinion company using quota sampling based on six geographic regions, three neighborhood types (urban, suburban, and rural), and selected socio-demographics (age, gender, race, ethnicity, presence of children, annual household income, student status and employment status); and
3. All respondents from the first wave of data collection in 2015 (N = 1975) were re-contacted through the same online opinion panel company.

The data contains extremely rich individual-level information on socio-demographic traits, attitudes towards a variety of topics, current travel behavior, driver's licensing, vehicle ownership and detailed information about the primary vehicle used (if any), access to all types of facilities (e.g., parking) and others.

The socio-demographic distribution of raw data mirrors the population statistics from the 2018 American Community Survey (ACS), with a slightly over-sampling of Caucasians, people aged 55 or over, those unemployed, households without children and residents living outside of Los Angeles regions and lower-density regions in California. To compensate for the non-response bias present in the raw data, a two-stage weighting process (cell-weighting + iterative proportional fitting) was implemented. The population target is based on the 2014–2018 US Census ACS 5-year estimates. Eight variables as shown in Table 1 (Column A) were selected, including region, neighborhood type, age, gender, race-ethnicity, household annual income, presence of children and

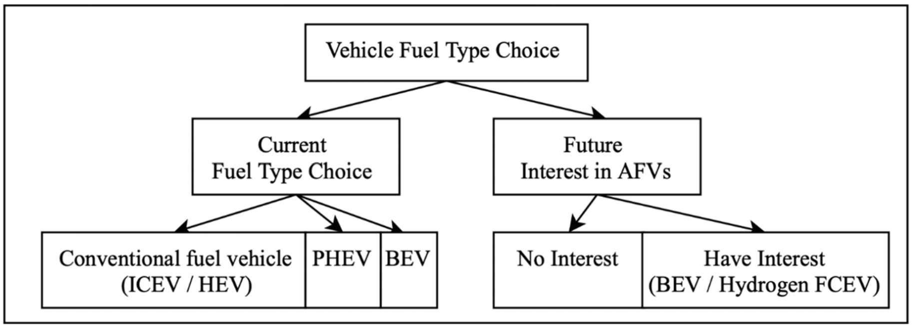

Fig. 2. Modeling Framework.

Table 2
Weighted Distribution of Combined Current & Future Fuel Type Choice.

Current Vehicle Fuel Type	**Weighted Sample (N)**	**Weighted Distribution (column-wise 100 %)**	**Interest in purchasing/leasing an AFV in the future (row-wise 100 %)**			
			No interest	**Have interest**		
				BEV only	**Hydrogen only**	**BEV & Hydrogen**
Conventional fuel vehicles	**3188**	**98.1 %**	60.7 %	21.7 %	2.5 %	15.1 %
ICEV	3003	92.4 %	62.0 %	21.3 %	2.3 %	14.4 %
HEV	185	5.7 %	39.1 %	28.5 %	5.9 %	26.5 %
PHEV	38	1.2 %	32.7 %	30.5 %	0.0 %	36.7 %
BEV	25	0.8 %	6.7 %	64.1 %	5.9 %	23.3 %
Total sample	3251	100 %	1949	719	82	501
% of total sample	–	–	59.9 %	22.1 %	2.5 %	15.4 %

student/employment status. The weighting process effectively reduces the gap between target marginal distributions (Column C) and those of the unweighted data (Column E), as the final gaps (Column J) are much smaller than the original differences (Column G). Despite the improved data consistency, small discrepancies still exist. For instance, in the weighted data, urban residents are still slightly over-represented, while suburban and rural residents are slightly under-represented. Overall, the weighted data is a good representation of the population in California (at least, based on observable characteristics of the individuals), though differences in unobserved characteristics of the respondents might still exist (as common for many similar studies too) due to the sampling and recruitment approaches that were used during the data collection. All descriptive analyses presented in this paper are weighted statistics.

3.2. Current vehicle fuel type choice & future interest in AFVs

Out of 3632 valid respondents after data cleaning, 3572 respondents reported that either themselves or their household members owned or leased at least one vehicle, 60 respondents only had regular vehicle access through someone else (e.g., friend, roommate) and 124 respondents had no regular vehicle access in their household. Considering only people from the first group may directly or indirectly be involved in the decision making of their personal/household vehicle fuel type choice, only those are considered in this study.

69 % of respondents in the research sample reported having more than one vehicle in the household. Therefore, they were asked to indicate the fuel type of the one vehicle that they used most often (*single choice out of seven fuel type options,* including gasoline, diesel, HEV, PHEV, BEV, FFV and FCEV), as well as their interest in buying/leasing an AFV in the future (*multi-choices out of four fuel type options*, including gasoline hybrid (i.e., HEV/ PHEV), BEV, FFV and FCEV). The original survey questions are listed below. Below we refer to these two variables as "*current vehicle fuel type choice*" and "*future interest in AFVs*", respectively.

Since most current FFVs still heavily rely on gasoline/diesel, they may not require much behavioral change of the drivers and may not make as much effect on the environments as other categories of AFV. Thus gasoline, diesel and FFV are all categorized as ICEVs. There is only one hydrogen FCEV current user, so it is excluded from the analyses. Note that our survey combines HEVs and PHEVs as "gasoline hybrid" when asking respondents' future interest in AFVs. Observations from "other"/ "I do not know" categories are also excluded from consideration.

Given the complexity of the survey data structure, Fig. 2 proposes a simplified modeling framework for this study. For the *current fuel type choice*, ICEVs and HEVs are combined as conventional fuel vehicles. PHEVs and BEVs are separate since they have a number of distinctions in terms of vehicle features, user experience, requirements for infrastructure and policy regulations. The *future interest in*

Table 3
Comparison of user characteristics across different current vehicle fuel type choice and future interest in AFVs.

	Variables	Categories	# of Cases	% of Case (column-wise %)	Current Fuel Type Choice (row-wise mean or %)			Future Interest in AFVs (row-wise mean or %)	
					Conventional fuel vehicle	PHEV	BEV	No Interest	Have Interest
	Latent Attitudes								
1	Pro-environment	(mean)	3251	100.0 %	−0.08	0.47	0.84	−0.24	0.19
2	Tech-savvy	(mean)	3251	100.0 %	−0.03	0.77	0.95	−0.23	0.31
3	Car-dependent	(mean)	3251	100.0 %	−0.09	0.24	−0.27	−0.10	−0.07
4	Car-utilitarian	(mean)	3251	100.0 %	0.05	0.27	0.75	−0.11	0.31
5	Pro-suburban	(mean)	3251	100.0 %	−0.02	0.14	−0.62	0.10	−0.20
	Socio-demographics								
6	Age	18–34	801	24.6 %	98.2 %	1.1 %	0.6 %	58.9 %	41.1 %
7		35–54	1170	36.0 %	98.0 %	1.4 %	0.6 %	54.4 %	45.6 %
8		55 or over	1280	39.4 %	98.0 %	1.0 %	1.0 %	65.6 %	34.4 %
9	Race	Non-White/ Caucasian	738	22.7 %	97.1 %	1.4 %	1.5 %	58.9 %	41.1 %
10		White/Caucasian	2513	77.3 %	98.3 %	1.1 %	0.6 %	60.2 %	39.8 %
11	Gender	Not-Male	1838	56.5 %	98.1 %	1.0 %	0.9 %	64.7 %	35.3 %
12		Male	1414	43.5 %	98.0 %	1.4 %	0.6 %	53.8 %	46.2 %
13	Student status	Not-Student	2720	83.7 %	98.5 %	0.8 %	0.7 %	61.2 %	38.8 %
14		Student	531	16.3 %	95.6 %	3.0 %	1.4 %	53.6 %	46.4 %
15	Employment	Unemployed	1248	38.4 %	99.0 %	0.5 %	0.5 %	69.3 %	30.7 %
16		Employed	2003	61.6 %	97.5 %	1.6 %	0.9 %	54.1 %	45.9 %
17	Education	Below college degree	1723	53.0 %	99.4 %	0.4 %	0.3 %	67.4 %	32.6 %
18		College degree or above	1528	47.0 %	96.6 %	2.1 %	1.3 %	51.5 %	48.5 %
19	Household income	below $50,000	1357	41.7 %	99.3 %	0.2 %	0.5 %	68.4 %	31.6 %
20		$50,000 to $99,999	1604	49.3 %	98.0 %	1.3 %	0.7 %	55.1 %	44.9 %
21		$100,000 or above	290	8.9 %	92.3 %	5.1 %	2.6 %	47.5 %	52.5 %
22	Household size	(mean)	3251	100.0%	2.80	3.33	2.82	2.78	2.85
	Residential Characteristics								
23	Neighborhood type	Rural	810	24.9 %	99.0 %	0.6 %	0.4 %	65.3 %	34.7 %
24		Suburban	1428	43.9 %	97.6 %	1.4 %	1.0 %	58.0 %	42.0 %
25		Urban	1013	31.2 %	97.9 %	1.3 %	0.8 %	58.4 %	41.6 %
26	Housing tenure	Rent	1403	43.2 %	99.2 %	0.5 %	0.3 %	60.7 %	39.3 %
27		Own	1848	56.8 %	97.2 %	1.7 %	1.1 %	59.3 %	40.7 %
28	Housing type	Apartment, condo, or others	847	26.0 %	99.7 %	0.3 %	0.0 %	63.9 %	36.1 %
29		Stand-alone/ attached house	2405	74.0 %	97.5 %	1.5 %	1.0 %	58.5 %	41.5 %
30	Residential parking	Unreserved, on-street parking or others	108	3.3 %	100.0 %	0.0 %	0.0 %	65.6 %	34.4 %
31		Private/reserved parking	3143	96.7 %	98.0 %	1.2 %	0.8 %	59.7 %	40.3 %
	Exposure to PEVs & PEV infrastructure								
32	# of BEV exposure within one mile at residential neighborhood	(mean)	3251	100.0 %	84	149	133	77	98
33	# of PHEV exposure within one mile at residential neighborhood	(mean)	3251	100.0 %	78	115	129	71	91
34	# of BEVs exposure at worksite	(mean)	3251	100.0 %	19,404	32,496	32,624	18,872	20,836
35	# of PHEVs exposure at worksite	(mean)	3251	100.0 %	17,400	24,299	32,639	16,892	18,657
36	Density of EV charging station at residential location	(mean)	3251	100.0 %	53.49	7.65	12.36	55.35	48.57
37	Distance to the nearest charging station at residential location	(mean)	3251	100.0 %	1.60	1.30	0.87	1.67	1.47

AFVs is condensed into a binary choice (i.e., no interest/ have interest) based on their interests in BEVs or hydrogen FCEVs, two fuel types that require the most “innovativeness” and are the main interests of California ZEV Mandate (California Air Resources Board, 2020). The current and future scenarios are modeled in two branches; however, their interrelationships will also be modelled and discussed in the coming sections.

After removing cases with missing values on variables of interest which will be discussed in Section 3.3 and Section 3.4, the weighted sample of our study is 3251 in the end. The weighted distribution of combined current and future fuel type choices is shown in Table 2. Note that our survey only asks for the ***most frequently used*** vehicle, thus the distributions for AFVs listed below should be lower than their actual market share in the state. Somewhat unsurprisingly, conventional fuel vehicles have been dominantly chosen by over 98 % of the respondents as their most frequently used vehicle, and more than 60 % show no interest in AFV in the future. Most current AFV users, especially BEV users, are much more open to alternative fuel options in the future. Pearson's Chi-squared tests suggest that the future interest in AFVs is significantly correlated with current fuel type choice.

Individuals' vehicle fuel type choice depends on the potential impacts on the natural and living environment. One may concern that our survey will likely result in social desirability bias (SDB) when respondents tend to give socially desirable responses instead of choosing responses that are reflective of their true feelings (Grimm, 2010). Compared to their self-reported current vehicle fuel type choice, their stated future interest may be more subject to SDB. Nevertheless, we believe this issue has been largely alleviated in our study: first, this is a self-administered survey without any presence involvement of an interviewer; second, the survey question only asks about respondents' interests rather than immediate purchase intention, and therefore they are less likely to provide answers under high pressure.

4. Descriptive analyses

This section will discuss a range of variables collected either from the survey or external sources postulated to be potential influencing factors on people's AFV adoption, including attitudes and lifestyles, socio-demographic characteristics, residential built environment characteristics, and exposure to AFVs and AFV infrastructure. Table 3 compares current AFV users and potential adopters in the future in a descriptive way using the weighted dataset.

4.1. Latent attitudes

To extract individuals' latent attitudes, we performed an exploratory factor analysis (EFA) based on attitudinal statements from the survey. To determine the optimal number of factors, we relied on the Kaiser criterion of computing eigenvalues for correlation matrix. The rule is to keep the factor scores with Eigen values greater than one (Gorsuch, 1983). In terms of the type of rotation, we tried both orthogonal rotation and oblique rotation. After trying different specifications, five factors derived from 21 attitudinal statements using orthogonal rotation generated the optimal solution with better practical interpretation. Because factor axes remain orthogonal to each other, those factors are uncorrelated. The results are presented in Table-A in the Appendix. The larger factor loadings correspond to a stronger relationship between the indicator and the corresponding latent factor.

The *pro-environment* factor encompasses individuals' positive attitudes towards governmental environmental regulations as well as personal environmentally friendly lifestyles. The *tech-savvy* variable reflects individuals' familiarity/proficiency with new technologies and their curiosity/openness to new experiences. The *car-utilitarian* factor pertains to individuals' value on the pragmatic aspects of a vehicle, such as taking more seriously on its functionality instead of its brand. *Car-dependent* factor indicates individuals' dependence on and attachment to their vehicle in daily life. Finally, the *pro-suburban* factor manifests individuals' preference to live in suburban areas to gain more spacious houses, even in exchange for better neighborhood services and public transportation.

Based on Table 3 (row 1–5), current AFV users and potential adopters tend to be more pro-environment, tech-savvy, and car-utilitarian. PEV users seem to share some commonalities but also have some differences in terms of attitudes. Those latent factors are hypothesized to have impacts on AFV adoption.

4.2. Socio-demographics

Based on Table 3 (row 6–22), regarding the current fuel type choice, students, employees, those more highly educated, and with higher income are more likely to adopt an AFV than their counterparts. For the future interest, it is clear that a substantial amount of people from all socio-demographic categories and built environments are willing to shift to an AFV, and yet the differences are also observed. For instance, although most current AFV owners live in a househod with annual income at least $100,000, a sizable percentage of population among median- and low-income households have in fact shown their future interest. Similar phenomenon exists among other population segments.

4.3. Neighborhood effects

Four additional variables were collected from external sources to reflect the neighborhood effects and infrastructure effects for each survey respondent.

4.3.1. Past exposure to PEVs at residential location and worksite

For PEV exposure at residential locations and worksites, we use the same data sources as the newly-published paper by Chakraborty et al. (2022). In short, the PEV exposure at the residential location was measured by the stock of PEVs within a 1-mile radius of the centroid of each census blockgroup where respondents resided. The data source is the vehicle registration data (October 2014 to December 2016) from the California Department of Motor Vehicles . The PEV exposure at the worksite was measured by the expected number of PEVs a regular commuter from each block group is exposed to at the worksite, based on the number of jobs, the number of commuters, and the origin–destination of commutes for each block group from the Longitudinal Employer-Household Dynamics

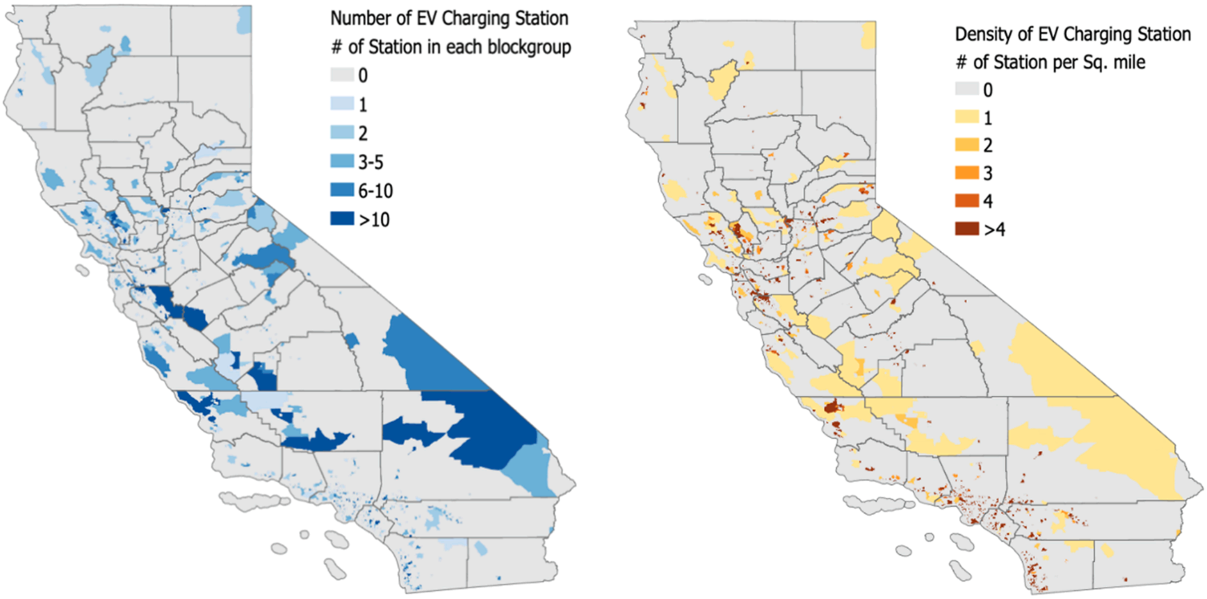

Fig. 3. Count and density of EV charging station at the block group level.

Origin-Destination Employment Statistics database.

These two variables are included in our model, aiming to capture the potential effects of social interaction with peers, neighbors, family, and coworkers. As Rogers (2010) argued, peers adopting a new technology can send an approval signal to others, and conformity encourages those people to adopt similar behaviors and lifestyles. Table 3 (row 32–35) suggests that current PEV users and potential adopters have higher PEV exposure in their neighborhoods and worksites than others. We thus hypothesize that the higher the exposure, the stronger the positive peer effect on people's EV adoption.

4.3.2. Density of public EV supply equipment (EVSE)

The EVSE density is measured by the number of PEV charging stations in each block group, combining Level 1, Level 2, and Level 3 (Direcet Current Fast Chargers) as plotted in Fig. 3. The original geocoded location of each EVSE was collected from the Alternative Fuels Data Center on the U.S. Department of Energy (DOE) website (US Department of Energy, 2020). By 2018 when the survey was conducted, 23,818 individual charging outlets were installed in 5,954 locations (i.e., stations) within California.

Previous studies have found that public charging can compensate for the unavailability of home charging and ease some concerns of car buyers (Axsen et al., 2010; Zou et al., 2020). Our study includes this variable to explore the public EVSE network effects on consumers' propensity to own or lease PEVs. In fact, our data as shown in Table 3 (row 36) suggests that current PEV vehicle users are located in areas equipped with lower EVSE. This is potentially because respondents in our data mainly rely on home chargers (see more explanations in Section 4.3.4).

There is sufficient evidence to support the claim that different types of EVSE have different effects. For example, fast chargers are more practical than slower chargers, especially during long-distance travel above vehicles' single-charge range (Neaimeh et al., 2017). Some chargers (e.g., Tesla superchargers) are more exclusive to certain user groups than public chargers. However, considering that this study focuses more on regular neighborhood-level travel activities, which can be potentially fulfilled by charging events supported by each type of EVSE and also the EVSE is still relatively sparse across the state,this study aggregates all available EVSE at the block group level without distinguishing their types.

4.3.3. Accessibility to EVSE

The accessibility to EVSE is measured by the Euclidean distance (mile) to the nearest EVSE from the home location of each respondent, which is one aspect of EV readiness. Even though only those PEV owners are using those facilities, we assume their existence can impact each respondent's decision-making and the utility of their current and future fuel type choice. Based on Table 3 (row 37), our data suggest that individuals with better access to EVSE are more likely to adopt PEVs.

4.3.4. Residential characteristics

According to an estimate by the U.S. DOE, more than 80 % of charging events occur at home, and thus public EVSE perhaps matters less to those individuals with home chargers. The availability of home chargers is most influential in encouraging EV adoption (e.g., Hardman et al., 2018). Unfortunately, respondents in our survey did not directly indicate whether any home chargers were available to them. To tackle with this limitation, four pieces of information related to residential ownership and built environment characteristics, including their neighborhood type (i.e., rural, suburban, urban), housing tenure (i.e., own, rent), housing type (i.e., house, apartment/

condo/others), and residential parking (i.e., private parking, on-street parking) are included in our modeling. They are expected to capture some heterogenous propensity of having reliable home charging in the household. For instance, Lee et al. (2019) found that more than 80 % of PEV adopters from 2012 to 2017 in California were homeowners. Also, charging in a single-family home, usually with a garage, is generally more convenient and allows EV owners to take advantage of incentives such as tax credit or rebates for home EVSE installation, and also obtain low and stable residential electricity rates for charging their vehicles in the long run. In comparison, charging at a multi-family home can be less reliable and more similar to the experience of using public charging. Only 20 % of current EVs are owned by occupants of multi-family dwellings, who therefore mostly rely on public charging. Based on Table 3 (row 28–31), our data does suggest that individuals living in suburban/urban areas and owning a house with private parking are more likely to currently adopt PEVs.

5. Modeling approach

Standard discrete choice models (DCM) based on random utility theory are widely used for modeling vehicle choice; however, a number of researchers have argued that a hybrid choice model (HCM), i.e., a model that integrates a DCM with a latent variable structural equations model, has a number of advantages. An HCM (or, alternatively, an integrated choice and latent variable, or ICLV model) allows a more explicit treatment of unobserved heterogeneity, greater behavioral realism, and increased statistical efficiency by incorporating additional behavior-related information from, e.g., measurement scale data on attitudes and perceptions. The enhanced behavioral representation is useful for extending policy relevance of quantitative models (Abou-Zeid and Ben-Akiva, 2014; Ben-Akiva et al., 2002; Vij and Walker, 2016; Walker and Ben-Akiva, 2011). Specifically, the ICLV model can incorporate psychometric latent factors (e.g., internal knowledge, opinion, perceptions, and attitudes) as explanatory variables, thus yielding a more behaviorally realistic model. It hypothesizes that both choice and attitudinal responses are influenced by the same latent factors, directly or indirectly, while at the same time, those latent factors themselves are affected by experience and external factors, such as the characteristics of the decision-makers. The ICLV model has been widely applied in various contexts, such as vehicle type choice (Bolduc and Alvarez-Daziano, 2010), vehicle fuel type choice (Alvarez-daziano and Bolduc, 2009), and shared mobility choices (Li and Kamargianni, 2020).

For this study a logit-kernel-based ICLV model has been constructed to simultaneously model the effects of individual characteristics, latent perceptions/attitudes, residential built environment characteristics, and the local context of the EV market on two different choices of respondents: *current vehicle fuel type*, and *interest in leasing/purchasing of a BEV/FCEV (i.e., "future interest")*. The model includes two multinomial/binomial logit-kernel sub-models for current choice (ICEV, PHEV, BEV) and future interest (No, Yes), respectively. These are conditional on five latent variables that are modeled by a structural equation, with a measurement equation that captures the effect of latent variables on responses to attitudinal questions. Details of the equations are provided below.

As Equation (1) suggests, the utilities for competing alternatives in the discrete choice sub-models depend on observed and latent variables associated with the decision-makers. Choice is determined by random utility maximization, as Equation (4) indicates. Our study assumes that socio-demographic characteristics influence choice not only through direct effects on utility, but also indirectly through the latent variables. These indirect effects occur via the structural equation (2), where each latent variable is expressed as a function of exogenous socio-demographic variables, including age, gender, race, education degree, student status, employment status, household size, and household income.

Equation (3) specifies the measurement equation, where the effects of unobservable latent variables are manifested in a total of 21 indicator variables from measurement scales in the survey. Respondents rate their level of agreement or disagreement with statements that reflect their opinions or attitudes. The indicators represent additional information that allows identification and interpretation of the latent variables. Initial decisions about the number of latent factors as well as the specification of the structural and measurement equations are based on the results of the EFA discussed earlier. The final model specification depends on statistical testing and inference using estimates of candidate ICLV models.

As noted, the structural equation (2) and measurement equation (3) support the identification of (unobserved) latent variables through their relationship to both observed socio-demographics and indicators, and by design these latent variables are hypothesized to include substantial information related to (unobserved) latent utilities for both current fuel type choice and future purchase intent. As such, estimated model parameters yield useful behavioral insights. Moreover, this integrated model captures key underlying effects that cause observed choices for current fuel choice and future interest to be correlated, which opens the possibility for correctly isolating potential experience effects.

Utility specification:

$$\mathrm{u_{mnj}} = \mathrm{B_m x_{nj}} + \Gamma_\mathrm{m} \mathrm{x_n^*} + \epsilon_\mathrm{mnj},\ \epsilon_\mathrm{mnj} \sim \ i.i.d. Gumbel \tag{1}$$

Structural equation:

$$\mathrm{x_n^*} = \mathrm{As_n} + \mathrm{v_n}, \mathrm{v_n} \sim \ N(0, \Phi) \tag{2}$$

Measurement equation:

$$i_n = Dx_n^* + \eta_n, \eta_n \sim N(0, \Psi) \tag{3}$$

Choice equation:

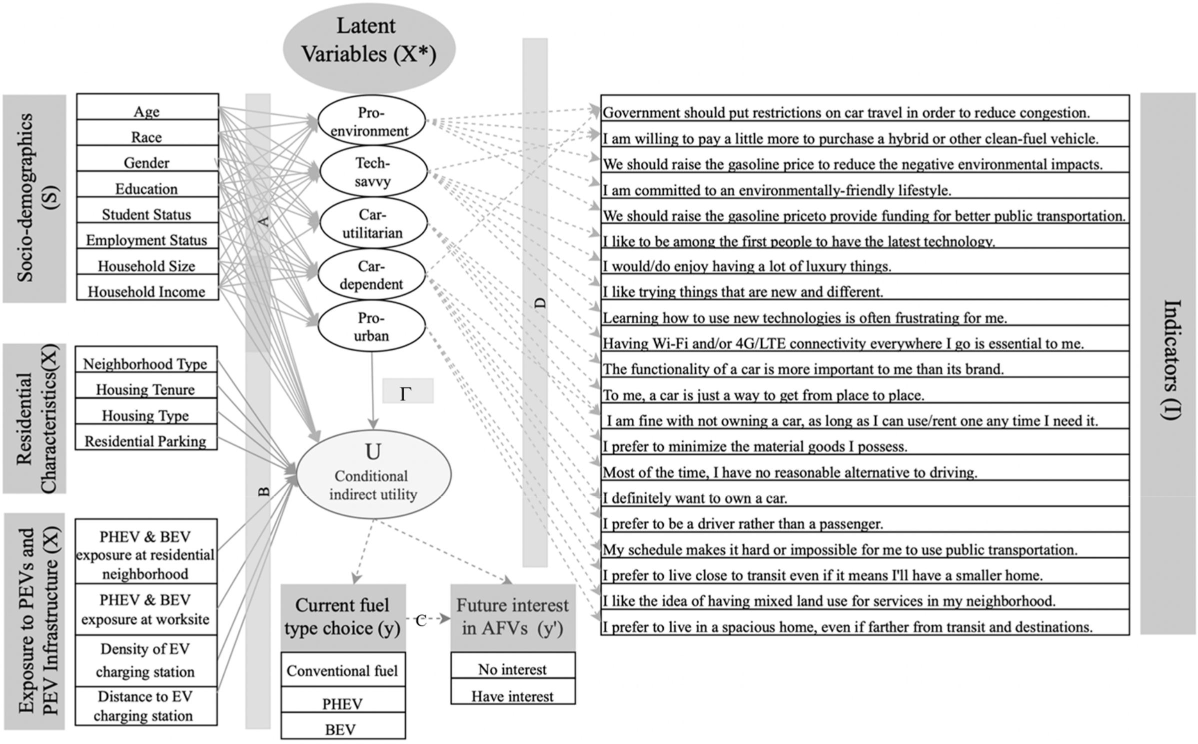

Fig. 4. ICLV model.

$$y_{mnj} = \begin{cases} 1, if\, u_{mnj} \geq u_{mnj'}, \forall j' \\ 0, otherwise \end{cases} \tag{4}$$

If,

J_{mn} denotes the number of mutually exclusive alternatives $j (j = 1,\dots, J_n)$ that are available to individual n in choice situation m (i.e., current choice and future interest).

X denotes the number of observable features of each alternative,

K denotes the number of observable socio-demographic features of individual n,

M denotes the number of latent factors x^*_n,

R denotes the number of indicators (Likert-scale attitudinal statements),

Then,

u_{nj} is a (J × 1) vector of the utility of alternative j for individual n,

x_{nj} is a (X × 1) vector of observable features of each available alternative to individual n,

B_m is a (J × X) matrix of the unknown regression coefficients between each observable feature and each alternative in choice situation m,

x^*_n is a (M × 1) vector of latent factors of individual n,

Γ_m is a (J × M) matrix of unknown regression coefficients between each latent factor and alternative in choice situation m,

ϵ_{mnj} is a (J × 1) vector of random disturbances of unobserved component with i.i.d. Gumbel distribution,

s_n is a (K × 1) vector of observable socio-demographic features of individual n,

A is a (K × M) matrix of the unknown regression coefficients between each socio-demographic feature and each latent factor,

v_n is a (M × 1) vector of random disturbances with normal distribution $N(0, \Phi)$,

Φ is a (M × M) variance–covariance matrix,

i_n is a (R × 1) vector of the level of the agreement to each attitudinal statement of individual n,

D is a (R × M) matrix of factor loadings indicating the relationship between each indictor and latent factor,

η_n is a (R × 1) vector of measurement errors with normal distribution $N(0, \psi)$,

ψ is a (R × R) diagonal matrix with variance terms on the diagonal,

y_{mnj} is the final choice of individual n among alternative J.

Fig. 4 illustrates the ICLV model for current fuel type choice and future interest with our hypothesized relationship based on initial factor analysis (see Appendix) and regression models for the measurement and structural models. We use the *Apollo* library in R for performing maximum simulated likelihood estimation (Hess and Palma, 2019).

Table 4
Estimation results from the measurement equation.

	Latent Factors									
	Pro-environment		Tech-savvy		Car-dependent		Car-utilitarian		Pro-Suburban	
	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.
1. We should raise the price of gasoline to provide funding for better public transportation.	**1.15**	**(57.11)**								
2. We should raise the price of gasoline to reduce the negative impacts on the environment.	**1.09**	**(52.35)**								
3. I am willing to pay a little more to purchase a hybrid or other clean-fuel vehicle.	**0.56**	**(25.84)**	**0.30**	**(12.93)**						
4. The government should put restrictions on car travel in order to reduce congestion.	**0.53**	**(22.36)**			**−0.38**	**(-14.49)**				
5. I am committed to an environmentally-friendly lifestyle.	**0.39**	**(22.67)**								
6. Having Wi-Fi and/or 4G/LTE connectivity everywhere I go is essential to me.			**0.61**	**(25.17)**						
7. I like to be among the first people to have the latest technology.			**0.63**	**(25.27)**						
8. I would/do enjoy having a lot of luxury things.			**0.37**	**(16.19)**						
9. I like trying things that are new and different.			**0.37**	**(20.01)**						
10. Learning how to use new technologies is often frustrating for me.			**−0.52**	**(-20.68)**						
11. Most of the time, I have no reasonable alternative to driving.					**0.52**	**(12.56)**				
12. My schedule makes it hard or impossible for me to use public transportation.					**0.45**	**(9.66)**				
13. I definitely want to own a car.					**0.46**	**(19.10)**				
14. I prefer to be a driver rather than a passenger.					**0.36**	**(11.05)**				
15. I am fine with not owning a car, as long as I can use/rent one any time I need it.					**−0.65**	**(-17.85)**	**0.34**	**(9.00)**		
16. To me, a car is just a way to get from place to place.							**0.67**	**(18.10)**		
17. The functionality of a car is more important to me than its brand.							**0.50**	**(16.51)**		
18. I prefer to minimize the material goods I possess.							**0.39**	**(11.11)**		
19. I prefer to live close to transit even if it means I'll have a smaller home and live in a more crowded area.									**−0.87**	**(-29.41)**
20. I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood.									**−0.55**	**(-20.25)**
21. I prefer to live in a spacious home, even if it is farther from public transportation and many places I go.									**0.58**	**(16.09)**

Note: Statistics in the table represent coefficients and robust *t*-statistics. They are all statistically significant at 99% confidence level.

Table 5
Estimation results from the structural equation.

Social-demographic Characteristics	Category	Latent Factors				
		Pro-environment	Tech-savvy	Car-dependent	Car-utilitarian	Pro-suburban
Age	35–54	−0.16	−0.38	0.04	−0.06	−0.07
(base: 18–34)		(−2.65)***	(−5.74)***	(0.58)	(−0.82)	(−1.13)*
	55 and	−0.21	−0.97	0.43	0.16	0.00
		(−3.57)***	(−13.20)***	(5.93)***	(2.32)**	(0.05)
Race	White/Caucasian	−0.12	−0.19	0.04	−0.07	0.16
(base: Non-white/Caucasian)		(−2.48)**	(−3.15)***	(0.69)*	(−1.16)	(2.77)**
Gender	Male	0.03	0.16	−0.04	−0.16	0.16
(base: Not-Male)		(0.71)	(2.94)***	(−0.68)	(−2.77)***	(2.59)***
Student Status	Student	0.19	0.50	−0.29	0.09	−0.33
(base: Not-Student)		(2.49)**	(5.88)***	(−3.39)***	(0.99)	(−4.34)***
Employment	Employed	−0.02	0.45	0.02	−0.04	−0.19
(base: Unemployed)		(−0.28)	(5.62)***	(0.26)	(−0.65)	(−3.44)***
Education	College and above	0.47	0.29	−0.32	0.29	−0.39
(base: Below college)		(9.67)***	(5.19)***	(−5.81)***	(4.68)***	(−7.07)***
Household Income	$50,000 to $99,999	0.09	0.07	0.03	−0.16	0.16
(base: below $50,000)		(1.66)	(1.04)	(0.47)	(−2.36)**	(2.46)**
	$100,000 and above	0.16	0.30	0.26	−0.34	0.31
		(2.58)**	(4.10)***	(3.51)***	(−4.32)***	(4.38)***
Household Size	(mean)	−0.05	0.04	−0.04	0.04	0.04
		(−3.60)***	(2.57)**	(−2.35)**	(2.09)**	(2.33)**

Note: Statistics in the table represent coefficients, robust *t*-statistics, statistical significance, and confidence level: *10%, **5%, ***1%.

6. Results

Multiple model specifications were tested, where the final model included explanatory variables that correspond to the list of variables in Table 3 and reflect hypotheses in Fig. 4.[2] The final model presented includes many significant coefficients at the 95 % level (i.e., p-value less than 0.05), and are partially in accordance with hypotheses in Fig. 4. In the results that follow, some explanatory variables appearing in Table 3 with insignificant coefficients have been dropped to save space. Although all the equations in an ICLV model are calibrated simultaneously, we present the results separately for each sub-model (e.g., measurement equation, structural equation, and two choice models). Note that an important advantage of this approach is that the simultaneous effects of unobserved latent variables on multiple outcome variables are now captured (in contrast to standard statistical analyses) in a way that at least partially addresses the problem of spurious correlation. Similarly, this approach includes effects of socio-demographics on choices that are both direct (through utility) and indirect (through attitudes) in contrast to standard discrete choice models.

6.1. *Structural model*

6.1.1. *Measurement equation*

Table 4 shows the coefficients of each indicator in the measurement equation, which suggest the relation between each of the five latent variables and the corresponding indicators. They are comparable to the factor loadings from the EFA and all are statistically significant.[3]

6.1.2. *Structural equation*

Table 5 shows the estimated coefficients for the structural equation, which confirms our hypothesis that exogenous socio-demographic attributes significantly influence people's perceptions and attitudes.

People who are younger, more highly educated, with higher income, and with a smaller household size are more *pro-environment* than their counterparts. Many of the above characteristics look alike among *tech-savvy* people, except that men, students, employees, and people with a larger household size are more *tech-savvy*. Non-white people are also more *pro-environment* and *tech-savvy*, this is consistent with some signs suggesting a potential digital transformation among the younger and a more racially diversified population (Enni et al., 2016). The findings for the *car-dependent* factor are consistent with expectations. People who are older with higher incomes are more *car dependent*. In contrast, students, and those who are more highly educated are less car dependent. Regarding *car-utilitarianism*, the pragmatic aspects of a vehicle seem to be of less concern to males and high-income individuals, potentially because they are more driven by other aspects of vehicles, such as representation of social status. At the same time, those who are older and more

[2] One technical aspect of these models is that, to identify the effect of unobserved latent variables, maximum simulated likelihood with normally distributed random variables is used. Part of the analysis required increasing the number of random draws to establish stability of the final estimates. In this work, final estimates used 300 random draws from a modified Latin hypercube sampling method.

[3] Indicators were standardized (mean-centered with a variance of one) to correspond to the structure of EFA. In addition to coefficients, standard deviations were also estimated but are not shown here to save space (they were all very close to one, as might be expected).

Table 6
Results from discrete choice models.

Variables	Categories	Current Fuel Type Choice (Conventional fuel vehicles as the baseline)		Future Interest in AFV (BEV/Hydrogen) (No interest as the baseline)
		PHEV	BEV	Has interest
Constants		−19.30	−7.38	−1.27
		(–23.24)***	(−5.18)***	(−4.24)***
Latent Factors				
Pro-environment		0.54	0.76	0.45
		(3.23)***	(3.87)***	(9.07)***
Tech-savvy		0.36	0.77	0.36
		(1.69)*	(3.23)***	(5.90)***
Car-dependent		0.32	0.14	0.06
		(1.18)	(0.57)	(0.91)
Car-utilitarian		0.03	−0.16	0.14
		(0.14)	(−0.67)	(2.19)**
Pro-suburban		0.24	0.41	0.03
		(1.15)	(2.01)**	(0.55)
Socio-demographics				
Age	35–54	−0.22	0.77	0.15
(base: 18–34)		(−0.50)	(1.66)*	(1.14)
	55 and above	0.05	1.18	0.07
		(0.09)	(1.34)	(0.42)
Race	White/Caucasian	0.38	0.20	0.18
(base: non-white/Caucasian)		(0.90)	(0.46)	(1.76)*
Gender	Male	0.28	0.06	0.34
(base: not-Male)		(0.91)	(0.20)	(4.19)***
Student status	Student	0.22	−0.91	−0.27
(base: non-student)		(0.44)	(−1.13)	(−1.93)*
Education	Colle	0.88	1.00	0.29
(base: below colleage degree)		(1.60)	(1.67)*	(3.20)***
Household size		0.16	−0.03	0.01
		(1.99)*	(0.22)	(0.31)
Annual household income	$50,000 to $99,999	0.60	0.20	0.25
(base: below $50,000)		(0.92)	(0.26)	(2.38)**
	$100,000 and above	0.68	0.82	0.54
		(1.08)	(1.08)	(4.48)***
Residential Characteristics				
Neighborhood type	Suburban	0.67	0.05	0.00
(base: Rural)		(1.29)	(0.09)	(0.00)
	Urban	0.42	0.54	−0.16
		(0.76)	(0.86)	(−1.25)
Housing tenure	Own	0.29	−0.04	−0.25
(base: Rent)		(0.73)	(−0.07)	(−2.44)**
Housing type	Stand-alone/attached house	1.24	0.14	0.01
(base: Apartment, condo, or others)		(1.69)*	(0.27)	(0.14)
Residential parking	Private/reserved parking	3.31	0.09	0.09
(base: Unreserved, on-street parking or others)		(8.40)***	(0.08)	(0.83)
Exposure to BEVs				
# of BEVs within one mile at neighborhood		−0.001	0.003	0.0003
		(−0.35)	(1.73)*	(0.47)
# of BEV exposure at worksite	Medium	0.82	1.84	0.19
(base: low)		(1.19)	(2.01)**	(0.77)
	High	1.10	2.25	0.33
		(1.29)	(2.03)**	(1.06)
Current User Experience				
Current user	PHEV user	–	–	0.58
(base: Conventional fuel vehicle user)		–	–	(1.56)**
	BEV user	–	–	1.38
		–	–	(2.60)**
# of Observation			3260 (Conventional: PHEV:BEV= 3172:47:41)	3260 (No: Yes= 1765:1495)
LL(0,choice)			−3581	−2259.7
LL(final, choice)			−411.9	−2002.8

Note: Statistics in the table represent coefficients, robust *t*-statistics, statistical significance, and confidence level: *10%, **5%, ***1%.

highly educated pay more attention to the pragmatic aspects of vehicles. Finally, in terms of residential location preference, those who are white, have higher incomes and larger household sizes are more *pro-suburban*, while students, employees, people with higher education are less so.

These findings identify key relationships between observable population characteristics and underlying attitudes that would otherwise be represented as “unobservable heterogeneity” using standard discrete choice modeling approaches. This has potentially important policy implications because observable socio-demographics are more actionable when it comes to understanding how groups might react differently to different policies, and how policies might be designed, tailored, and efficiently targeted.

6.2. Fuel type choice model

Table 6 reports the results from the two logit models with interrelated dependent variables (one for current fuel type choice, and the other for future interest in leasing/purchasing AFVs). For current fuel type choice, the base alternative is conventional fuel. The alternative specific constants (ASCs) are negative for both PHEVs and BEVs, indicating that these options are less likely to be chosen for respondents with mean-level attitudes, and base-level characteristics (18–34 years old, female, non-student, no college degree, etc.). Similarly, the ASC for future interest is also negative (although less so) for people with the same characteristics.

6.2.1. Latent attitudes

Model results suggest that people who are more *pro-environment* and *tech-savvy* are more prone to currently having PEVs as their most frequently used vehicle, and these attitudes similarly apply to leasing/purchasing AFVs in the future. These two types of attitudes have been used in many prior studies in other regions in the US and abroad and our results are consistent with them (Daziano and Bolduc, 2013; Jansson et al., 2009, 2017; Jenn et al., 2018; Jensen et al., 2013; Jin et al., 2020; Rezvani et al., 2015; Soto et al., 2018; Tanwir and Hamzah, 2020).

People who are more *car-dependent* and *car-utilitarian* do not show statistically significant differences for PHEVs and BEVs for current vehicle fuel choice. One might hypothesize that, at the very least, people purchasing BEVs prior to and including 2018 might be less “car-dependent.” Moreover, the corresponding average score for car-dependence is indeed negative (although small) in Table 3. However, an ICLV model estimates a wide range of effects simultaneously, potentially addressing any issues with correlation that might occur when using standard summary statistics. Interestingly, the coefficient for car-utilitarian has a positive, statistically significant coefficient for the interest in a future AFV purchase. This initially seems counter-intuitive. When evaluating a future AFV purchase, one might expect individuals who view cars in more utilitarian terms to possibly harbor *negative* expectations about AFV characteristics such as practicality, reliability, purchase cost, range, fuel availability. However, these results suggest that Californians in 2018 with car-utilitarian attitudes are *more* likely indicate an interest in future AFVs. This indicates that, at the very least, there appears to be a perception among individuals with this attitude that AFVs will be feasible (utilitarian) choices in the future. It might even be that individuals have increased awareness and knowledge of such characteristics as lower operating cost, faster acceleration, and convenience of home recharging.

Finally, we found that *pro-suburban* is associated with the *current* use of BEVs. As discussed above, those individuals who are more likely to own a spacious home are automatically in a better position to set up and use home charging infrastructure.

6.2.2. Socio-demographics

The effect of socio-demographic variables on latent variables was discussed earlier, as was the effect of latent variables on the dependent variables of interest. These results together demonstrate that there are many indirect effects of socio-demographics on the two dependent variables of interest. However, we found that, for current fuel type choice, direct socio-demographic effects were weak at best, once indirect effects have been taken into account. In contrast, a number of direct effects on interest in the future purchase of an AFV. Men, whites, people who are well educated, with higher-income, and non-students are more likely to have an interest in future purchase of an AFV than their counterparts.

6.2.3. Residential characteristics

As with socio-demographics, we found very few direct effects associated with residential characteristics. As before, underlying attitudes associated with the choice of residential location (e.g., those relating to tradeoff of home size versus access to transit) might already capture key aspects of current fuel choice and future interest in an AFV. The strongest effect is that choice of a PHEV is strongly associated with *having private/reserved parking.* There is also some indication that suburban location and living in a detached home could play a role (although these are not clearly significant). This is consistent with results in the study by Axsen and Kurani (2012), who find that apartment residents with fewer private garages have lower home charger access. However, similar effects on current BEV adoption and interest in future AFVs are not statistically significant. Moreover, these results show a statistically significant negative effect of residence ownership on expressing interest in a future AFV. This result is inconsistent with our expectations, and warrants further investigation.

6.2.4. Exposure to PEVs and PEV infrastructure

Our study included efforts to identify neighborhood or peer effects, since these are an important part of the theory on diffusion of innovation. As explained, we merged additional variables that had been constructed for this purpose in another study (Chakraborty et al., 2022). Like their study, exposure to BEVs at both the residence and workplace locations is found to be statistically significant in explaining current fuel choice, but the strength of the effects are marginal. These exposure effects were not found to be statistically

Table 7
Potential AFV market penetration conditional on current vehicle fuel type.

Income category	Current Vehicle Fuel Choice	Future Interest in AFVs	Penetration
Low-income	Conventional fuel	No	67.0 %
		Yes	33.0 %
	PHEV	No	62.5%
		Yes	37.5 %
	BEV	No	60.6 %
		Yes	39.4 %
Middle-income	Conventional fuel	No	55.1 %
		Yes	44.9 %
	PHEV	No	50.8 %
		Yes	49.2 %
	BEV	No	49.6 %
		Yes	50.4 %
High-income	Conventional fuel	No	39.7 %
		Yes	60.3 %
	PHEV	No	37.2 %
		Yes	62.6 %
	BEV	No	37.2 %
		Yes	62.8 %

significant for interest in future purchase of AFVs. We also included exposure variables for PHEVs, but none were found to be statistically significant.

Other variables from the supply side, including *density of EV charging station* and *distance to the nearest charging station* are not statistically significant for both current and future fuel choices in this study. Here are potential reasons. (a) PEV users in our sample dominantly live in stand-alone/attached houses with private/reserved home parking, and thus we can infer that charging at home usually meets their needs. Some of them may also have access to chargers at the worksite. As a result, public charging may not play an essential role when our survey was conducted among our respondents. For the future decision, we would not expect many of those who do not currently own an EV or are not seriously considering purchasing/leasing an EV to have good knowledge or even be aware of EVSE. (b) Given the early phase of the EV market and infrastructure deployment, it is likely that those current users and potential adopters are more driven by other internal factors, such as socio-demographics, values, attitudes, and perceptions associated with owning an EV as discussed above, instead of the direct utility from these external factors.

6.2.5. *Current user experience*

In our ICLV model we included direct effects for current use BEV and PHEV as explanatory variables for interest in a future AFV purchase. The rationale is that having actual experience with either a PHEV or a BEV would increase the propensity to be interested in a future AFV purchase. Both coefficients were positive, with the BEV effect being larger than PHEV. This consistent with findings from a recent study (Ling et al., 2021).

Note that, when estimating effects of this type, there is a concern that a statistically significant result could be spurious, due to correlations induced by unobserved heterogeneity. In this case, the result could be misinterpreted as an experience effect. One reason for employing the ICLV methodology is to address such issues by using a modeling framework that incorporates a substantial amount of attitudinal information in a way that captures unobserved heterogeneity. As a test, we took our final model and added a normally distributed random error component with coefficients for PHEV, BEV, and interest in future AFV purchase (as might be used in mixed multinomial logit) to capture any residual underlying heterogeneity. The estimated model was not significantly different from the final model based on a likelihood ratio test ($p = 0.20$).

6.3. *Potential market penetration*

The estimated final model can be used to produce in-sample predictions of potential AFV adoption (BEVs and Hydrogen FCEVs) for the whole market in the state of California by using weights created to match Census-based demographic statistics. The result of this calculation is that the percentage of the 2018 California population interested in an AFV purchase is estimated to be 41.4 % (with a 98 % confidence interval of 41.1 % – 41.7 %). Note that our survey did not specify a timeline when asking respondents' future interest, thus, we consider 41.4 % an estimate of maximum potential.

Further, we can also estimate the proportion of potential AFV adopters among specific population segments, which is conditional on the current vehicle fuel type. For instance, Table 7 makes such a comparison among individuals from different income categories. Unsurprisingly, while only 33 % of low-income conventional fuel vehicle users show interest in AFVs (i.e., the lowest among all groups), 63 % of high-income PEV users show interest in AFVs. Similar analyses can be extended to other socioeconomic profiles capture the total effect of other factors on AFV adoption.

7. Conclusion & policy recommendations

Based on 2018 California Panel Survey data, this study explores on how latent attitudes, socio-demographics, and neighborhood

Table A1
Results from exploratory factor analysis (5 factors from 21 attitudinal statements with orthogonal rotation).

	Latent Factors				
	Pro-environment	Tech-savvy	Car-dependent	Car-utilitarian	Pro-Suburban
1. We should raise the price of gasoline to provide funding for better public transportation.	0.85				
2. We should raise the price of gasoline to reduce the negative impacts on the environment.	0.89				
3. I am willing to pay a little more to purchase a hybrid or other clean-fuel vehicle.	0.43	0.32			
4. The government should put restrictions on car travel in order to reduce congestion.	0.45		−0.32		
5. I am committed to an environmentally-friendly lifestyle.	0.37				
6. Having Wi-Fi and/or 4G/LTE connectivity everywhere I go is essential to me.		0.54			
7. I like to be among the first people to have the latest technology.		0.65			
8. I would/do enjoy having a lot of luxury things.		0.38			
9. I like trying things that are new and different.		0.51			
10. Learning how to use new technologies is often frustrating for me.		−0.38			
11. Most of the time, I have no reasonable alternative to driving.			0.43		
12. My schedule makes it hard or impossible for me to use public transportation.			0.43		
13. I definitely want to own a car.			0.53		
14. I prefer to be a driver rather than a passenger.			0.34		
15. I am fine with not owning a car, as long as I can use/rent one any time I need it.			−0.52	0.31	
16. To me, a car is just a way to get from place to place.				0.51	
17. The functionality of a car is more important to me than its brand.				0.48	
18. I prefer to minimize the material goods I possess.				0.45	
19. I prefer to live close to transit even if it means I'll have a smaller home and live in a more crowded area.					−0.41
20. I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood.					−0.43
21. I prefer to live in a spacious home, even if it is farther from public transportation and many places I go.					0.65

effects (related to residential characteristics, and exposure to AFVs) may impact current and subsequent AFV adoption. In addition to summary statistics, we construct an ICLV model to jointly model current vehicle fuel type choice and future interest in AFVs within a framework that incorporates detailed attitude measurements to address unobserved heterogeneous preference effects that are potentially substantial. The following conclusions emerge.

The results suggest that individuals who are more *pro-environment* and *tech-savvy* are more likely to be currently using a PHEV or BEV, and that these attitudes will continue to play a role in developing an interest in purchasing an AFV in the future. Qualitatively, this finding is, of course, entirely consistent with other studies in other regions of the US and abroad (Jenn et al., 2018; Jin et al., 2020; Tanwir and Hamzah, 2020). However, our results also suggest that in 2018 many individuals who had not yet adopted an AFV had, nevertheless, reached a stage where, given their current state of awareness and knowledge, they expected to be interested in a future AFV purchase. In particular, those exhibiting an attitude of car-utilitarianism had a higher likelihood of expressing an intent to purchase. This attitude is characterized by viewing cars primarily in terms of their practicality for delivering mobility, where functionality is more important than brand. This suggests that AFVs in California may have reached a stage where they are no longer viewed as “exotic” or “risky” technologies, but realistic, practical, and perhaps an inevitable part of California’s future.

However, interestingly, individuals who are male, older (over 55), and with higher income are lower than average on car-utilitarianism, and therefore these socio-demographic factors should have an indirect effect of lowering interest in future AFVs. At the same time, being male and higher income has a positive, direct effect on future interest. Being college educated has both an indirect and direct positive effect on future interest.

This group (i.e., males, individuals with high income and college educated) has been found in our study and previous studies to be more likely to adopt AFVs (Carley et al., 2013; Hsu and Fingerman, 2021; Sovacool et al., 2018). However, it is noteworthy that in our study these factors lack statistical significance as direct effects for explaining current PEV choices, once key attitudes (pro-environment, tech-savvy, and for BEVs, pro-suburban) have been taken into account. In examining the structural equations, these three demographic characteristics (male, high-income, college educated) affect these attitudes in a variety of ways so that, while their net indirect effects might be consistent with increased AFV adoption, the relationships are complex. However, note that the overall impact of socio-demographics can be determined more clearly by using the in-sample prediction approach demonstrated in Section 6.3.

Focusing again on future intention, key factors taken together are a combination of pro-environment, tech-savvy, college educated, and high income (and also male). In other words, environmental concerns, interest in technology, and education, which have often been associated with early adopters, are continuing to play a role in this process. However, it is important to understand more clearly the role of income, once the other factors are taken into account. Our modeling approach supports this type of analysis, so the effect of income can be viewed as isolated from other factors that it might otherwise be correlated with. This suggests that perceptions of AFVs as high-priced alternatives may have played a role for Californians assessing their interest in future AFV purchases in 2018. Finding a way to lower the perceived purchase price of AFVs continues to be important.

This finding is entirely consistent with recent decisions by the State of California to aggressively address issues of equity and the potential impact on disadvantaged communities of policies supporting a transition to AFVs. While there is a range of AFV financial incentives, subsidy policies, and income tax credits enacted by federal and local governments to encourage AFV buyers, many do not account for these concerns. Identifying equity issues concealed in those programs and developing policies to better target beneficiaries may lead to higher adoption across more consumer segments, and increased social benefits overall (Liu et al., 2022).

Our results also tend to confirm prior results for current fuel type choices. We did not find a strongly significant *direct* effect of living in stand-alone/attached houses on current usage of PHEVs or BEVs (nor did this affect future interest). However, BEV ownership is related to a pro-suburban attitude that focuses on ownership of spacious homes. We did observe a strong direct effect of private/reserved parking for those using PHEVs most often (but no similar direct effect for BEV usage).[4] Taken altogether, these results are consistent with the need for dedicated, private space for home charger installation. In contrast, it is common for residences in multi-unit dwellings to share space, such as parking or electrical infrastructure, which makes charger installation harder. One way of mitigating this problem is to provide increased access to public chargers, and this has generally been viewed as a high priority by policy makers at both the state and federal levels.

Having said this, we were unable to find direct statistical evidence of the impact of public chargers on PEV usage in this study. At the same time, this is a challenging problem and researchers have generally found empirical evidence for this linkage to be elusive, despite its assumed importance. A recent exception is Chakraborty et al. (2022), who used a different methodology employing very large datasets of vehicle counts from vehicle registration data. Other recent studies suggesting that public charging infrastructure is a stimulus to EV diffusion include Egnér and Trosvik (2018) and Schulz and Rode (2022). However, one caveat is that most of those studies were conducted in much more mature regions, such as Sweden and Norway. While California is the nation's largest market for electric vehicles with about a third of the nation's public charging stations, the impact of those chargers on consumers and their payback periods are still largely uncertain. Our study, based on survey data with a relatively small number of respondents who use PEVs, may have been somewhat limited in its ability to detect this relationship. However, future similar studies with a combination of larger sample sizes and increased penetration of PEVs might be more successful.

In a similar vein, we also explored the possibility of neighborhood and peer effects, which diffusion of innovation theory suggests is important in the dynamics of market creation. Specifically, theory suggests that direct exposure to newly introduced products will increase awareness and knowledge by those in direct, physical proximity, accelerating the likelihood of additional adoption. We introduced measures of PEV exposure linked to both residential location and their associated worksites. In this instance, we found statistical evidence that exposure to BEVs at both residential and worksite locations increases the chances of a respondent being a current BEV user. In contrast to Chakraborty et al, (2022), effects involving PHEV exposure were not significant. In any case, these results tend to support a major rationale for government policies supporting introduction of AFVs, i.e., that such policies can accelerate the dynamics of penetration, particularly those that are oriented toward enhancing awareness (e.g., encouraging more hands-on test driving either as a driver or passenger (Ling et al., 2021)). Previous studies have shown evidence of changes in attitudes and perceptions toward AFVs after real-life experience with using them (A. Jensen et al., 2014; A. F. Jensen et al., 2013).

Finally, using our modeling results combined with sampling weights, we project that 41.4 % of the population (adults) in California may show interest in AFVs in the future, which can be viewed as a proxy for estimated maximum market penetration. This suggests that there is still notable untapped potential to increase the market share of AFVs based on attitudes and perceptions of Californians in 2018. This is entirely consistent with the sales increases observed over the past four years. Moreover, our projections indicate that the penetration will most likely differ among different population segments, with current high-income PEV users leading the way. However, our survey did not specify a timeline when asking respondents' future interest in AFVs, and thus some individuals may report based on their short-time expectations, while others may report based on their long-term expectations.

There are some limitations of this study. First, the survey asked respondents to report the fuel type of the vehicle that is "used most often." Because of range limitations and lack of charging stations, AFVs often play a specific and limited role in meeting a household's travel needs, and may not necessarily be the "most used" vehicle. In fact, our data suggests that current AFV users are more likely to have more than one vehicle in the household. Asa result, our survey was not structured to capture the full role of PEVs in the population, but among those frequent daily users who would have the highest level of familiarity with the PEVs. Second, while we included an extensive list of variables in our model, as noted at the outset we did not study the specific effects of vehicle features (such as purchase price, charging time, and driving range) which have generally been found to have substantial impacts on consumers' AFV adoption. However, most of these studies have relied on methodologies using hypothetical vehicle descriptions (e.g., discrete choice experiments). Instead, our study specifically relied on the current beliefs and expectations developed by respondents based on their actual experiences in an evolving market. The results and insights from this study can form the basis for future efforts that include the role of vehicle features, but within a context of real-world market experiences. Third, as noted previously, PEV users only account for a small fraction of our sample, and thus the power of analysis for some items was restricted. With the growing uptake of AFVs in California, similar studies with a larger sample size can capture additional insight into the dynamics of market penetration over time. Finally, from survey design's standpoint, some survey questions can be better designed to avoid potential ambiguity. For instance, HEVs and PHEVs were combined as "gasoline hybrid" vehicles in our survey when we asked respondents their future interest in AFVs. We recommend having them separate in the survey questions and modeling process in the future.

[4] Oddly, we found a statistically significant effect suggesting that residence ownership has a negative effect on future interest in purchasing AFVs. This is nominally inconsistent with the expectation that homeowners might be more inclined to consider AFVs because of the relative ease of home recharging. Of course, there are other possible correlates to home ownership, and this result warrants further investigation.

CRediT authorship contribution statement

Xiatian Iogansen: Conceptualization, Data curation, Methodology, Formal analysis, Visualization, Software, Validation, Writing – original draft, Writing – review & editing. **Kailai Wang:** Conceptualization, Data curation, Writing – original draft, Writing – review & editing. **David Bunch:** Conceptualization, Methodology, Software, Supervision, Formal analysis, Validation, Writing – review & editing. **Grant Matson:** Data curation, Writing – review & editing. **Giovanni Circella:** Funding acquisition, Project administration, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This study was funded by the National Center for Sustainable Transportation, which receives funding from the US Department of Transportation [grant number 69A3551747114] through the University Transportation Centers Program and the California Department of Transportation [grant number 65A0527 for data collection and grant number 65A0686 for data analyses] . Additional funding was provided by the 3 Revolutions Future Mobility Program of the University of California, Davis. We extend our sincere gratitude to Farzad Alemi, Yongsung Lee, Ali Etezady, Leticia Pineda, Diego Bernal, Rosaria Berliner, Sung Hoo Kim, Junia Compostella, Jai K Malik, Niloufar Yousefi, and Kate Tiedeman for their efforts on data collection and data cleaning to make this research possible.

Appendix A

Table A1

References

Abou-Zeid, M., Ben-Akiva, M., 2014. Hybrid choice models. In: *Handbook of Choice Modelling,* pp. 383–412. doi: 10.4337/9781781003152.00025.

Al-Alawi, B.M., Bradley, T.H., 2013. Review of hybrid, plug-in hybrid, and electric vehicle market modeling Studies. Renew. Sustain. Energy Rev. 21, 190–203. https://doi.org/10.1016/j.rser.2012.12.048.

Alvarez-daziano, R., Bolduc, D., 2009. *Canadian consumers ' perceptual and attitudinal responses toward green automobile technologies: an application of Hybrid Choice Models Introduction: Hybrid Choice Modeling.*

Anable, J., 2005. "Complacent Car Addicts"; or "Aspiring Environmentalists"? Identifying travel behaviour segments using attitude theory. Transp. Policy 12 (1), 65–78. https://doi.org/10.1016/j.tranpol.2004.11.004.

Axsen, Jonn, Kurani, Kenneth S, 2012. Interpersonal Influence within Car Buyers' Social Networks: Applying Five Perspectives to Plug-in Hybrid Vehicle Drivers. Environment and Planning A: Economy and Space 44 (5), 1047–1065. https://doi.org/10.1068/a43221x. In this issue.

Axsen, J., Kurani, K.S., Burke, A., 2010. Are batteries ready for plug-in hybrid buyers? Transp. Policy 17 (3), 173–182. https://doi.org/10.1016/j.tranpol.2010.01.004.

Bansal, P., Kumar, R.R., Raj, A., Dubey, S., Graham, D.J., 2021. Willingness to pay and attitudinal preferences of Indian consumers for electric vehicles. Energy Econ. 100, 105340 https://doi.org/10.1016/j.eneco.2021.105340.

Ben-Akiva, M., Mcfadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., Bolduc, D., Boersch-Supan, A., Brownstone, D., Bunch, D.S., Daly, A., De Palma, A., Gopinath, D., Karlstrom, A., Munizaga, M.A., 2002. Hybrid Choice Models: Progress and Challenges. Market. Lett. 13 (3), 163–175.

California Air Resources Board, 2020. Zero-Emission Vehicle Program. *California Air Resources Board*. Retrieved from https://ww2.arb.ca.gov/our-work/programs/zero-emission-vehicle-program.

Bolduc, D., Alvarez-Daziano, R., 2010. On Estimation of Hybrid Choice Models. In: *Choice Modelling: The State-of-the-art and The State-of-practice*. 10.1108/9781849507738-011.

Bolduc, Denis, Boucher, Nathalie, Alvarez-Daziano, Ricardo, 2008. Hybrid Choice Modeling of New Technologies for Car Choice in Canada. Transportation Research Record 2082 (1), 63–71. https://doi.org/10.3141/2082-08. In this issue.

Breetz, H.L., Salon, D., 2018. Do electric vehicles need subsidies? Ownership costs for conventional, hybrid, and electric vehicles in 14 US cities. Energy Policy 120, 238–249.

Bunch, D.S., Bradley, M., Golob, T.F., Kitamura, R., Occhiuzzo, G.P., 1993. Demand for clean-fuel vehicles in California: A discrete-choice stated preference pilot project. Transp. Res. Part A 27 (3), 237–253. https://doi.org/10.1016/0965-8564(93)90062-P.

Carley, S., Krause, R.M., Lane, B., Graham, J.D., 2013. Intent to purchase a plug-in electric vehicle: a survey of early impressions in large US cites. Transport. Res. Part D: Transport Environ. 18, 39–45.

Chakraborty, D., Bunch, D.S., Brownstone, D., Xu, B., Tal, G., 2022. Plug-in electric vehicle diffusion in California: Role of exposure to new technology at home and work. Transp. Res. Part A 156, 133–151. Retrieved from 10.1016/j.tra.2021.12.005.

Circella, G., Matson, G., Alemi, F., Handy, S., 2019. Panel Study of Emerging Transportation Technologies and Trends in California: Phase 2 Data Collection. National Center for Sustainable Transportation, UC Davis. Retrieved from https://escholarship.org/uc/item/35x894mg.

Collantes, Gustavo, Sperling, Daniel, 2008. The origin of California's zero emission vehicle mandate. Transportation Research Part A: Policy and Practice 42 (10), 1302–1313. https://doi.org/10.1016/j.tra.2008.05.007. ISSN 0965-8564, In this issue.

Dallen, J., 2007. Sustainable transport, market segmentation and tourism: The Looe Valley Branch Line Railway, Cornwall, UK. *J. Sustain. Tourism* 15 (2), 180–199. https://doi.org/10.2167/jost636.0.

Danielis, R., Giansoldati, M., Rotaris, L., 2018. A probabilistic total cost of ownership model to evaluate the current and future prospects of electric cars uptake in Italy. Energy Policy 119, 268–281.

Daziano, R.A., Achtnicht, M., 2012. Forecasting Adoption of Ultra-Low-Emission Vehicles Using the GHK Simulator and Bayes Estimates of a Multinomial Probit Model. SSRN Electron. J. https://doi.org/10.2139/ssrn.2013279.

Daziano, R.A., Bolduc, D., 2013. Incorporating pro-environmental preferences towards green automobile technologies through a Bayesian hybrid choice model. Transportmetrica A: Transport Sci. 9 (1), 74–106.

Egbue, O., Long, S., 2012. Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions. Energy Policy 48, 717–729. https://doi.org/10.1080/23311916.2020.1796198.

Egnér, F., Trosvik, L., 2018. Electric vehicle adoption in Sweden and the impact of local policy instruments. Energy Policy 121, 584–596.

Enni, L L., Ar, A.L.S., Als, L.L.E., 2016. African-American Millennials are Tech-savvy leaders in Digital Advancement. *Nielsen*. Retrieved from https://www.nielsen.com/us/en/insights/article/2016/african-american-millennials-are-tech-savvy-leaders-in-digital-advancement/.

Evadoption, 2022. EV Market Share – California. Retrieved from https://evadoption.com/ev-market-share/ev-market-share-california/.

Galván, Janer, Cantillo, Victor, Arellana, Julian, 2016. Factors Influencing Demand for Buses Powered by Alternative Energy Sources. Journal of Public Transportation 19 (2), 23–37. https://doi.org/10.5038/2375-0901.19.2.2. In this issue.

Ghasri, M., Ardeshiri, A., Rashidi, T., 2019. Perception towards electric vehicles and the impact on consumers' preference. Transport. Res. Part D: Transport Environ. 77, 271–291. https://doi.org/10.1016/j.trd.2019.11.003.

Giacomo, F., Noussan, M., 2021. Electric vehicle charging network in Europe: An accessibility and deployment trends analysis. Transport. Res. Part D: Transport Environ. 94, 102813.

Glerum, Aurélie, Stankovikj, Lidija, Thémans, Michaël, Bierlaire, Michel, 2014. Forecasting the Demand for Electric Vehicles: Accounting for Attitudes and Perceptions. Transportation Science 48 (4), 483–499. https://doi.org/10.1287/trsc.2013.0487. In this issue.

Gorsuch, R., 1983. Factor analysis, 2nd ed. Lawrence Erlbaum Associates, Hillsdale, NJ.

Grimm, P., 2010. Social Desirability Bias. In: *Wiley International Encyclopedia of Marketing*. 10.1002/9781444316568.wiem02057.

Hardman, S., Jenn, A., Tal, G., Axsen, J., Beard, G., Daina, N., Figenbaum, E., Jakobsson, N., Jochem, P., Kinnear, N., Plötz, P., Pontes, J., Refa, N., Sprei, F., Turrentine, T., Witkamp, B., 2018. A review of consumer preferences of and interactions with electric vehicle charging infrastructure. Transport. Res. Part D: Transport Environ. 62, 508–523.

Helveston, J.P., Liu, Y., Feit, E.M.D., Fuchs, E., Klampfl, E., Michalek, J.J., 2015. Will subsidies drive electric vehicle adoption? Measuring consumer preferences in the U.S. and China. Transport. Res. Part A: Policy Pract. 73, 96–112. https://doi.org/10.1016/j.tra.2015.01.002.

Hess, S., Palma, D., 2019. Apollo: A flexible, powerful and customisable freeware package for choice model estimation and application. J. Choice Modell. 32, 100170.

Hsu, C.-W., Fingerman, K., 2021. Public electric vehicle charger access disparities across race and income in California. Transp. Policy 100, 59–67.

Jansson, J., Marell, A., Nordlund, A., 2009. Elucidating green consumers: A cluster analytic approach on proenvironmental purchase and curtailment behaviors. J. Euromarketing 18 (4), 245–267. https://doi.org/10.1080/10496480903364242.

Jansson, J., Pettersson, T., Mannberg, A., Brännlund, R., Lindgren, U., 2017. Adoption of alternative fuel vehicles: Influence from neighbors, family and coworkers. Transport. Res. Part D: Transport Environ. 54, 61–73. https://doi.org/10.1016/j.trd.2017.04.012.

Jenn, A., Laberteaux, K., Clewlow, R., 2018. New mobility service users' perceptions on electric vehicle adoption. Int. J. Sustain. Transport. 12 (7), 526–540.

Jensen, A.F., Cherchi, E., Mabit, S.L., 2013. On the stability of preferences and attitudes before and after experiencing an electric vehicle. Transport. Res. Part D: Transport Environ. 25, 24–32. https://doi.org/10.1016/j.trd.2013.07.006.

Jensen, A., Cherchi, E., Ortúzar, J.D., 2014. A long panel survey to elicit variation in preferences and attitudes in the choice of electric vehicles. Transportation 41 (5), 973–993. Retrieved from 10.1007/s11116-014-9517-6.

Jin, F., Yao, E., An, K., 2020. Understanding customers' battery electric vehicle sharing adoption based on hybrid choice model. J. Cleaner Prod. 258, 120764. Retrieved from 10.1016/j.jclepro.2020.120764.

Jung, J., Yeo, S., Lee, Y., Moon, S., Lee, D.J., 2021. Factors affecting consumers' preferences for electric vehicle: A Korean case. Res. Transport. Business Manage. 41 (May) https://doi.org/10.1016/j.rtbm.2021.100666.

Kim, Jinhee, Rasouli, Soora, Timmermans, Harry, 2014. Expanding scope of hybrid choice models allowing for mixture of social influences and latent attitudes: Application to intended purchase of electric cars. Transportation Research. Part A: Policy and Practice 69, 71–85. https://doi.org/10.1016/j.tra.2014.08.016. In this issue.

Lee, J.H., Hardman, S.J., Tal, G., 2019. Who is buying electric vehicles in California? Characterising early adopter heterogeneity and forecasting market diffusion. Energy Res. Social Sci. 55, 218–226. https://doi.org/10.1016/j.erss.2019.05.011.

Li, W., Kamargianni, M., 2020. An integrated choice and latent variable model to explore the influence of attitudinal and perceptual factors on shared mobility choices and their value of time estimation. Transport. Sci. 54 (1), 62–83. https://doi.org/10.1287/trsc.2019.0933.

Ling, Z., Cherry, C.R., Wen, Y., 2021. Determining the Factors That Influence Electric Vehicle Adoption: A Stated Preference Survey Study in Beijing, China. *Sustainability (Switzerland)* 13 (21), 11719.

Liu, H., Dai, Z., Rodgers, M.O., Guensler, R., 2022. Equity issues associated with U.S. plug-in electric vehicle income tax credits. Transport. Res. Part D: Transport Environ. 102, 103159.

Liu, Z., Song, J., Kubal, J., Susarla, N., Knehr, K.W., Islam, E., Nelson, P., Ahmed, S., 2021. Comparing total cost of ownership of battery electric vehicles and internal combustion engine vehicles. Energy Policy 158, 112564.

Mabit, S.L., Cherchi, E., Jensen, A.F., Jordal-Jørgensen, J., 2015. The effect of attitudes on reference-dependent preferences: Estimation and validation for the case of alternative-fuel vehicles. Transport. Res. Part A: Policy Pract. 82, 17–28. https://doi.org/10.1016/j.tra.2015.08.006.

Manca, F., Sivakumar, A., Daina, N., Axsen, J., Polak, J.W., 2020. Modelling the influence of peers' attitudes on choice behaviour: Theory and empirical application on electric vehicle preferences. Transport. Res. Part A: Policy Pract. 140 (August), 278–298. https://doi.org/10.1016/j.tra.2020.08.016.

Morton, C., Anable, J., Nelson, J.D., 2016. Exploring consumer preferences towards electric vehicles: The influence of consumer innovativeness. Res. Transport. Bus. Manage. 18, 18–28. https://doi.org/10.1016/j.rtbm.2016.01.007.

Musti, S., Kockelman, K.M., 2011. Evolution of the household vehicle fleet: Anticipating fleet composition, PHEV adoption and GHG emissions in Austin, Texas. Transport. Res. Part A: Policy Pract. 45 (8), 707–720. https://doi.org/10.1016/j.tra.2011.04.011.

Neaimeh, M., Salisbury, S.D., Hill, G.A., Blythe, P.T., Scoffield, D.R., Francfort, J.E., 2017. Analysing the usage and evidencing the importance of fast chargers for the adoption of battery electric vehicles. Energy Policy 108, 474–486. https://doi.org/10.1016/j.enpol.2017.06.033.

Ogden, J.M., Williams, R.H., Larson, E.D., 2004. Societal lifecycle costs of cars with alternative fuels/engines. Energy Policy 32 (1), 7–27. https://doi.org/10.1016/S0301-4215(02)00246-X.

Potoglou, D., Kanaroglou, P.S., 2007. Household demand and willingness to pay for clean vehicles. Transport. Res. Part D: Transport Environ. 12 (4), 264–274. https://doi.org/10.1016/j.trd.2007.03.001.

Qian, L., Grisolía, J.M., Soopramanien, D., 2019. The impact of service and government-policy attributes on consumer preferences for electric vehicles in China. Transport. Res. Part A: Policy Pract. 122, 70–84.

Rezvani, Z., Jansson, J., Bodin, J., 2015. Advances in consumer electric vehicle adoption research: A review and research agenda. Transport. Res. Part D: Transport Environ. 34, 122–136. https://doi.org/10.1016/j.trd.2014.10.010.

Rezvani, Z., Jansson, J., Bengtsson, M., 2018. Consumer motivations for sustainable consumption: The interaction of gain, normative and hedonic motivations on electric vehicle adoption. Business Strategy Environ. 27 (8), 1272–1283. https://doi.org/10.1002/bse.2074.

Rogers, 2010. Diffusion of Innovations, 4th. Simon and Schuster, New York. In this issue.

Schulz, F., Rode, J., 2022. Public charging infrastructure and electric vehicles in Norway. Energy Policy 160, 112660.

Shaheen, S., Martin, E., Totte, H., 2020. Zero-emission vehicle exposure within U.S. carsharing fleets and impacts on sentiment toward electric-drive vehicles. Transp. Policy 85, 23–32. https://doi.org/10.1016/j.tranpol.2019.09.008.

She, Z., Sun, Q., Ma, J., Xie, B., 2017. What are the barriers to widespread adoption of battery electric vehicles? A survey of public perception in Tianjin, China. Transp. Policy 56, 29–40.

Sierzchula, W., Bakker, S., Maat, K., Van Wee, B., 2014. The influence of financial incentives and other socio-economic factors on electric vehicle adoption. Energy Policy 68, 183–194. https://doi.org/10.1016/j.enpol.2014.01.043.

Soto, J.J., Cantillo, V., Arellana, J., 2014. Hybrid choice model for alternative fuelled vehicles. Interciencia 39 (9), 666–673.

Soto, J.J., Cantillo, V., Arellana, J., 2018. Incentivizing alternative fuel vehicles: the influence of transport policies, attitudes and perceptions. Transportation 45 (6), 1721–1753. https://doi.org/10.1007/s11116-018-9869-4.

Soto, J.J., Cantillo, V., Arellana, J., 2021. Market segmentation for incentivising sustainable transport policies. Transport. Res. Part D: Transport Environ. 99, 103013 https://doi.org/10.1016/j.trd.2021.103013.

Sovacool, B.K., 2009. Early modes of transport in the United States: Lessons for modern energy policymakers. Policy Soc. 27 (4), 411–427. https://doi.org/10.1016/j.polsoc.2009.01.006.

Sovacool, B.K., Kester, J., Noel, L., de Rubens, G.Z., 2018. The demographics of decarbonizing transport: The influence of gender, education, occupation, age, and household size on electric mobility preferences in the Nordic region. Global Environ. Change 52, 86–100. Retrieved from 10.1016/j.gloenvcha.2018.06.008.

Tanaka, M., Ida, T., Murakami, K., Friedman, L., 2014. Consumers' willingness to pay for alternative fuel vehicles: A comparative discrete choice analysis between the US and Japan. Transport. Res. Part A: Policy Pract. 70, 194–209. https://doi.org/10.1016/j.tra.2014.10.019.

Tanwir, N.S., Hamzah, M.I., 2020. Predicting Purchase Intention of Hybrid Electric Vehicles: Evidence from an Emerging Economy. World Electric Vehicle J. 11 (2), 35.

US Department of Energy, 2020. Alternative Fueling Station Locator. *US Department of Energy*. Retrieved from https://afdc.energy.gov/stations/#/find/nearest.

Valeri, E., Cherchi, E., 2016. Does habitual behavior affect the choice of alternative fuel vehicles? Int. J. Sustain. Transport. 10 (9), 825–835. https://doi.org/10.1080/15568318.2016.1163445.

Vij, A., Walker, J.L., 2016. How, when and why integrated choice and latent variable models are latently useful. Transport. Res. Part B: Methodol. 90, 192–217. https://doi.org/10.1016/j.trb.2016.04.021.

Walker, J.L., Ben-Akiva, M., 2011. Advances in discrete choice: Mixture models. In: *A Handbook of Transport Economics,* pp. 160–187. doi: 10.4337/9780857930873.00015.

Wang, X.W., Cao, Y.M., Zhang, N., 2021. The influences of incentive policy perceptions and consumer social attributes on battery electric vehicle purchase intentions. Energy Policy 151, 112163. https://doi.org/10.1016/j.enpol.2021.112163.

Zou, T., Khaloei, M., MacKenzie, D., 2020. Effects of Charging Infrastructure Characteristics on Electric Vehicle Preferences of New and Used Car Buyers in the United States. Transport. Res. Record: J. Transport. Res. Board 2674 (12), 165–175.