

# Electric Vehicle Adoption Behavior and Vehicle Transaction Decision: Estimating an Integrated Choice Model with Latent Variables on a Retrospective Vehicle Survey

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## Abstract

Electric vehicles (EVs) promise a sustainable solution to mitigating negative emission externalities of transportation systems caused by fossil-fueled conventional vehicles (CVs). While recent developments in battery technology and charging infrastructure can help evolve the niche market of EVs into the mass market, EVs are yet to be widely adopted by the public. This calls for an in-depth understanding of public adoption behavior of EVs as one dimension of vehicle decision making, which itself may be intertwined with other vehicle decision-making dimensions, especially vehicle transaction. This study presents an integrated choice model with latent variables (ICLV) to investigate households'—as a decision-making unit—decisions on vehicle transaction type (i.e., no transaction, sell, add, and trade) and vehicle fuel type (i.e., CVs and all EV types, including hybrid EV, plug-in hybrid EV, and battery EV) choice. To analyze the ICLV model empirically, one of the first revealed preferences national vehicle survey involving CVs and all EV types was conducted, which retrospectively inquired about 1,691 American households' dynamics of vehicle decision making and demographic attributes over a 10-year period as well as their attitudes/preferences. The model estimation results highlight that EV adoption and vehicle transaction choice is influenced mainly by (1) the dynamics of household demographic attributes and (2) four latent constructs explaining attentiveness to vehicle attributes, social influence, environmental consciousness, and technology savviness. Notably, EV adoption promotion policies are found to be likely most effective on socially influenced individuals, who tend to consider advertisement and social trend more when making vehicle decisions.

## Keywords

demand estimation, planning and analysis, transportation demand forecasting, traveler behavior and values

Car-oriented societies face various negative externalities such as traffic congestion, transportation infrastructure inequity, noise pollution, and air pollution (1–3). Particularly in the United States, light-duty vehicles contribute to nearly 15% of greenhouse gas emissions (4) and an annual congestion cost of \$101 billion for delay time and wasted fuel estimated in almost 500 urban areas (5). A sustainable solution to diminishing these negative externalities can be the substitution of conventional gasoline and diesel vehicles (CVs) with electric vehicles (EVs), which include hybrid EV (HEV), plug-in HEV (PHEV), and battery EV (BEV). The major barriers to

the large-scale adoption of EV, especially plug-in EV (PEV) that collectively refers to both PHEV and BEV, are found to be the limited electric driving range, long charging time, and the poor provision of charging

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infrastructure (6, 7). These barriers are rapidly overcome by technological enhancements, such as in battery technology (8), leading to the recent introduction of affordable long range (200 + miles) BEV (9), as well as policy decisions on charging infrastructure deployment (9).

Despite its growing uptake (9, 10), the low market share of EV in the United States and globally may, however, postpone achieving the sustainability goal through large-scale EV adoption. This calls for research on EV adoption behavior at the disaggregate level (e.g., the household as the unit of decision making), which is also suggested by a relevant review study (11). One approach to such disaggregate-level models looks at the problem through the lens of psychology, which indeed relies merely on unobserved (latent) subjective factors—such as attitudes, perceptions, emotions, and symbolism—to assess intention to adopt and use EV (see Rezvani et al. [12] for a review). The second approach is based on economics through estimating discrete choice models to investigate EV adoption behavior in a comparative setting with CVs, which provides a suitable framework to evaluate policy effectiveness (11). The latter approach is further capable of complementing the former by incorporating the latent subjective attitudes and preferences into the choice model, thus explicitly accounting for taste heterogeneity through the underlying observed indicators. This model is called “integrated choice with latent variables” (ICLV) and was originally introduced by Ben-Akiva and Boccara (13) and Ben-Akiva et al. (14). The other choice models implicitly treating taste heterogeneity are mixed logit, which allows parameters to have a continuous random distribution over the sample (15, 16), and latent class, which approximates the underlying continuous random distribution of the parameters with a discrete one (17). The application examples of the former and latter in the context of EV adoption behavior, respectively, are Jia and Chen (18) and Qian et al. (19), and Khan et al. (20).

In the context of EV adoption behavior, the studies implementing the ICLV model mostly use stated preferences (SP) datasets to explore how latent attitudes, perceptions, and preferences shape an individual’s interest in various EV types. Ghasri et al. (21) considered three latent constructs capturing perception of BEV design with respect to performance, reliability, and aesthetic, environmental impacts, and safety. The findings highlight that a higher perception of BEV design leads to a higher probability of BEV adoption. Moreover, more attention to environmental aspects of BEV makes individuals more sensitive to electric driving range. Also, people who believe in greater safety of EV are more inclined toward large vehicle body types. Liao et al. (22) defined three latent constructs explaining pro-convenience, pro-ownership, and pro-EV leasing. The results highlight that

those who are interested in BEV prefer vehicle leasing the most and battery leasing the least. In contrast, purchasing the vehicle is favorable to people interested in CV and PHEV.

Bansal et al. (23) defined three latent constructs characterizing attitudes toward climate doubt (i.e., not believing in the climate impacts of EV and human behavior), EV tech belief (i.e., trusting EV technology), and early adoption (i.e., adopting EV at low market penetration). Estimated on a SP dataset collected in India, the study findings reveal that the climate doubters are negatively affected by BEV price being higher than CV price. Moreover, the early adopters are influenced by operating cost and driving range of BEV, although they are willing to pay more for BEV than CV. The results also reveal that the inclination of EV tech believers toward BEV is affected by electric driving range and BEV price relative to those of CVs. In a recent research, Li et al. (24) defined three latent psychological factors on environmental awareness, perceived environmental benefits, and subjective norms. They found that interest in EV adoption decision is influenced by market-oriented incentives—particularly policies on personal carbon trading and tradable driving credit—through economic motivations rather than latent factors. Nazari et al. (25) defined a latent construct on green travel pattern. Their empirical study using a revealed preferences (RP) dataset revealed the elasticity of only those who are attracted to PHEV with respect to the latent green travel pattern.

The studies reviewed above verify the explanatory power of the ICLV model in the context of EV adoption behavior, which is beyond the typical choice alternative attributes and demographic factors, through incorporating the decision makers’ latent subjective attitudes and preferences into the choice process (see Singh et al. [7] for a review study on factors affecting EV adoption behavior). Thus, the present study adopts the ICLV method to explore EV adoption behavior by investigating vehicle fuel type choice with a comprehensive choice set, including CV, HEV, PHEV, and BEV. Vehicle fuel type choice is one dimension of vehicle decision making that might be made simultaneously with other dimensions of vehicle decision making, especially vehicle transaction choice (for a review study on vehicle decision modeling, see Anowar et al. [26]). For instance, a household’s decision on EV adoption may be affected by whether an EV will be traded for an existing household vehicle or added to the household vehicle inventory. The answer might also have implications on the vehicle ownership level, in addition to the consequent short-term travel/activity pattern and long-term residential location choice (27, 28). The scarcity of the relevant literature, according to the summary of the recent studies using discrete choice models

**Table 1.** Recent Studies (2017–2022) Applying Discrete Choice Models to Investigate EV Adoption Behavior

Study	Location	Model	Method					Dataset					
			Fuel type alternatives				Joint decision		RP	SP	Retrospective		
			CV	HEV	PHEV	BEV	Yes	No			Yes	No	
Li et al. (24)	China	ICLV	✓	x	x	x	x	✓	x	✓	x	✓	Environmental awareness, perceived environmental benefits, and subjective norms
Bansal et al. (23)	India	ICLV	✓	x	x	✓	x	✓	✓	x	✓	✓	Climate doubt, EV tech belief, early adoption
Khan et al. (20)	Canada	LCM	✓	✓	✓	✓	x	✓	✓	x	x	✓	na
Jia and Chen (18)	United States	MLM	✓	✓	✓	✓	x	✓	x	✓	x	✓	na
Li et al. (29)	China	MLM, LCM	✓	x	x	✓	x	✓	✓	x	x	✓	na
Liao et al. (22)	Netherlands	MNL, MLM, ICLV	✓	x	✓	✓	x	✓	✓	x	✓	✓	Pro-convenience, pro-ownership, pro-EV leasing
Liu et al. (30)	United States	Binary logit	✓	x	x	✓	x	✓	✓	x	x	✓	na
Qian et al. (19)	China	MLM	✓	x	✓	✓	x	✓	x	✓	x	✓	na
Ghasri et al. (21)	Australia	ICLV	x	x	x	✓	x	✓	x	✓	x	✓	BEV design, environmental impacts, and safety
Nazari et al. (25)	United States	ICLV	✓	✓	✓	✓	x	✓	x	✓	x	✓	Green travel pattern
Kwon et al. (31)	South Korea	MNL	x	x	x	✓	x	✓	x	✓	x	✓	na
Smith et al. (32)	Australia	B-W	✓	x	x	✓	x	✓	x	✓	x	✓	Environmental concerns, excitement for new technologies, perceived usefulness, subjective norms
Cirillo et al. (33)	United States	MLM	✓	✓	x	✓	✓	x	✓	✓	x	x	na
Javid and Nejat (34)	United States	Binary logit	✓	x	x	✓	x	✓	x	✓	x	✓	na
Present study	United States	ICLV	✓	✓	✓	✓	✓	✓	✓	✓	x	✓	Vehicle attribute attentiveness, social influence, environmental consciousness, tech saviness

Note: SP = stated preferences; RP = revealed preferences; DCM = discrete choice model; MNL = multinomial logit model; MNL = mixed logit model; ICLV = integrated choice model with latent variables; B-W = best/worst model; HEV = hybrid electric vehicle; PHEV = plug-in hybrid electric vehicle; BEV = battery electric vehicle; na = not applicable.

presented in Table 1, confirms the need for research on the joint decisions on vehicle fuel and transaction type.

In view of this, the first contribution of the present study is analyzing the simultaneous decision of households—as the unit of decision making—on vehicle fuel type (including CV and a comprehensive set of EV types comprising HEV, PHEV, and BEV) and vehicle transaction type (including no transaction, sell, add, and trade). To our knowledge and as evidenced in Table 1, the simultaneous modeling of vehicle fuel type and vehicle transaction type, while also considering comprehensive choice sets for fuel and transaction types, has not been addressed in prior work. This has important policy implications, since most existing EV adoption policies launched globally are generally based on a one-size-fits-all approach, which may not be equally effective to promote EV adoption across distinct vehicle fuel types, distinct vehicle transaction types leading to EV adoption, and distinct consumers with heterogenous socioeconomic and latent attitudinal profiles. To accomplish the first contribution, one integrated component of the proposed ICLV model is a structural equation model (SEM) with latent variables, which explains attitudes toward vehicle decision making and lifestyle preferences through the underlying measurement indicators as well as socioeconomic characteristics. The second integrated component is a vehicle fuel type and transaction choice model explaining the decision process as a function of the latent attitudes and preferences along with vehicle attributes and dynamics of demographic attributes.

The second contribution of this study relates to the dataset used for the empirical analysis. The majority of the relevant studies using discrete choice models for understanding EV adoption behavior resort to SP datasets, according to the summary of the literature presented in Table 1. However, estimating a choice model on a RP dataset yields more realistic results than a SP dataset by describing EV adoption behavior (e.g., Javid and Nejat [34], Nazari et al. [25, 35], and Liu et al. [30]) rather than intention to adopt EV (e.g., Liao et al. [22], Nazari et al. [36], Li et al. [29], Jia and Chen [18], Bansal et al. [23], and Li et al. [24]). The latter group using SP datasets might cause hypothetical bias, referring to discrepancies between choices determined by the data and people's actual choice in the market (37). Therefore, the present study empirically analyzed the ICLV model using a RP national vehicle survey conducted in 2018, which retrospectively inquired about 1,691 U.S. households' vehicle decision making and dynamics of their demographic attributes over a 10-year period. To the best of the authors' knowledge, the retrospective feature of the dataset is also rarely observed in the relevant literature (Table 1).

The paper is organized as follows. The next section presents the methodology of ICLV, followed by a section

on the statistical analysis of the nationwide retrospective vehicle survey (RVS) collected in this study. The empirical model estimation results and policy implications are discussed next. The paper concludes with a summary of the research.

## Methodology

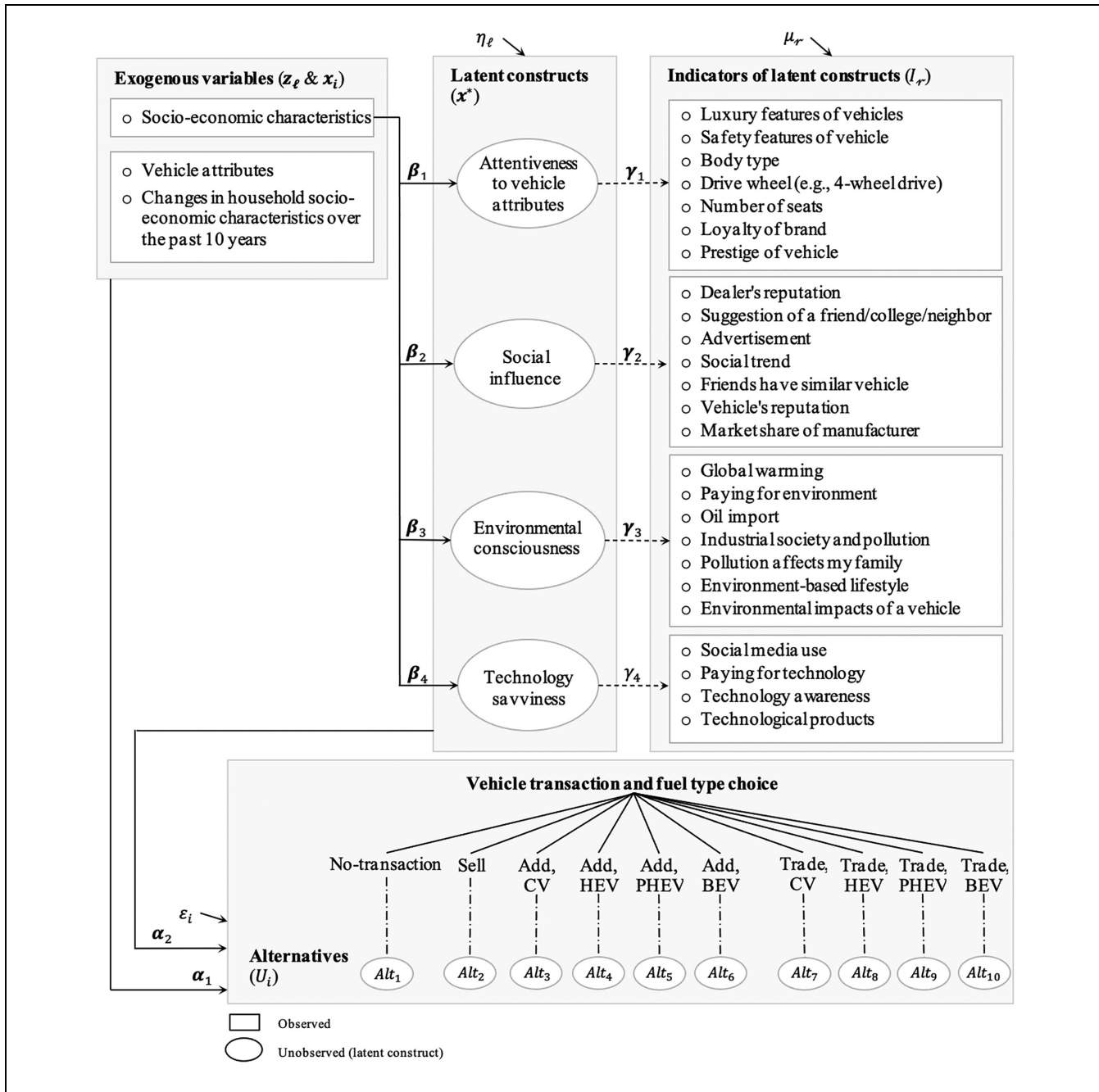
Figure 1 shows the overarching modeling framework of the ICLV model, which includes two integrated components estimated simultaneously. The first component is a SEM with latent variables determining four latent constructs, which are built on the underlying observed indicators via the measurement equations (shown by the dashed arrows in the upper section of Figure 1), as well as the explanatory variables through the structural equations (shown by the solid arrows in the upper section of Figure 1). The second component is a multinomial logit (MNL) model, which explains the decision process on vehicle transaction and fuel type with the choice set of 10 alternatives (shown in the lower section of Figure 5). The rest of this section presents the formulation of the ICLV model (13, 14). For brevity, the index  $q \in \{1, 2, \dots, Q\}$  for observations (i.e., vehicle fuel type and transaction decision) is suppressed in the equations.

The structural equations connect the vector of the latent constructs  $\mathbf{x}^* = (x_1^*, x_2^*, \dots, x_L^*)$  to the vector of the explanatory variables  $\mathbf{z}_\ell$ . This relationship for the  $\ell$ th latent construct  $x_\ell^*$ ,  $\ell \in \{1, 2, \dots, L\}$ , is formulated as Equation 1, which yields  $L$  structural equations. In this equation,  $\mathbf{z}_\ell$  is a  $S \times 1$  vector of explanatory variables for the  $\ell$ th latent construct, and  $\boldsymbol{\beta}_\ell$  is the corresponding vector of parameters. The unobserved factors of the  $\ell$ th structural equation are captured by the random error term  $\eta_\ell$ , which is assumed to be standard normally distributed (i.e.,  $\boldsymbol{\eta} \sim N[0, \boldsymbol{\Sigma}_\eta]$ , where  $\boldsymbol{\Sigma}_\eta$  is the covariance matrix). The probability of the structural equations is written as Equation 2:

$$x_\ell^* = \boldsymbol{\beta}_\ell' \mathbf{z}_\ell + \eta_\ell \quad \forall \ell \in \{1, 2, \dots, L\} \quad (1)$$

$$f_1(\mathbf{x}^* | \mathbf{z}; \boldsymbol{\beta}, \boldsymbol{\Sigma}_\eta) = \prod_{\ell=1}^L \frac{1}{\sigma_{\eta_\ell}} \phi\left(\frac{x_\ell^* - \boldsymbol{\beta}_\ell' \mathbf{z}_\ell}{\sigma_{\eta_\ell}}\right). \quad (2)$$

The measurement equations are formulated as Equation 3, where  $I_r, r \in \{1, 2, \dots, \mathcal{R}\}$  denotes the  $r$ th attitudinal/perceptual/preferential indicator, and thus there are  $\mathcal{R}$  measurement equations. The weight of the vector of the latent constructs  $\mathbf{x}^*$  on the  $r$ th indicator is denoted by  $\boldsymbol{\gamma}_r$ . The random errors of the  $r$ th measurement equation is denoted by the term  $\mu_r$  and is assumed to be standard normally distributed (i.e.,  $\boldsymbol{\mu} \sim N[0, \boldsymbol{\Sigma}_\mu]$ , where  $\boldsymbol{\Sigma}_\mu$  is the covariance matrix). The probability of the measurement equation is written as Equation 4:



**Figure 1.** Framework of the integrated choice with latent variables (ICLV) model for vehicle fuel type and transaction decisions.

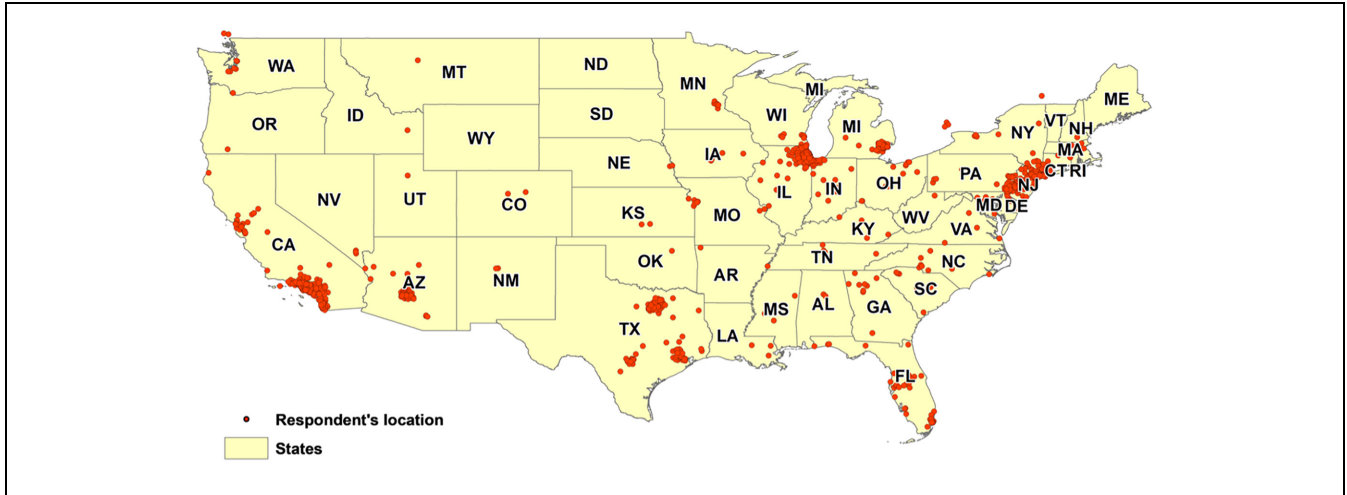
$$I_r = \gamma_r' x^* + \mu_r \quad \forall r \in \{1, 2, \dots, \mathcal{R}\} \quad (3)$$

$$U_i = \underbrace{\alpha_{1i}' x_i + \alpha_{2i}' x^*}_{V_i} + \varepsilon_i \quad y_i = 1, \text{ if } U_i = \max_j \{U_j\}. \quad (5)$$

$$f_2(I|x^*; \gamma, \Sigma_\mu) = \prod_{r=1}^{\mathcal{R}} \frac{1}{\sigma_{\eta_r}} \phi\left(\frac{I_r - \gamma_r' x^*}{\sigma_{\eta_r}}\right). \quad (4)$$

In the MNL model, the utility of alternative  $i$  ( $U_i$ ) is formulated as Equation 5, given the set of alternatives  $i \in \{1, 2, \dots, I\}$ , the  $\bar{\mathcal{S}} \times 1$  vector of explanatory variables ( $x_i$ ), and the  $\mathcal{L} \times 1$  vector of latent constructs  $x^*$ :

The model estimation yields the  $\bar{\mathcal{S}} \times 1$  vector of parameters for the explanatory variables  $\alpha_{1i}$  and the  $\mathcal{L} \times 1$  vector of parameters for the latent constructs  $\alpha_{2i}$ . The error term for alternative  $i$  is denoted by  $\varepsilon_i$ , which has standard Gumbel distribution  $\varepsilon \sim G[0, \Sigma_\varepsilon]$ , where  $\Sigma_\varepsilon$  is the covariance matrix, and  $y_i$  is the choice indicator, equaling



**Figure 2.** Locations of respondents to retrospective vehicle survey in the United States.

1 if a decision maker selects alternative  $i$  that maximizes the related utility equation. The vector of the choice indicators is denoted by  $y$ . The choice probability is derived as Equation 6:

$$f_3(y|x, x^*; \alpha_1, \alpha_2) = \frac{e^{V_i}}{\sum_{j \in I} e^{V_j}}. \quad (6)$$

The ICLV likelihood Equation 8 is the joint probability of the MNL model and the structural and measurement equations, as in Equation 7:

$$\begin{aligned} \text{Likelihood}(y, I|x; \alpha_1, \alpha_2, \beta, \gamma, \Sigma_\varepsilon, \Sigma_\eta, \Sigma_\mu) \\ = \int f_1(\cdot) \times f_2(\cdot) \times f_3(\cdot) dx^* \end{aligned} \quad (7)$$

$$\begin{aligned} L(y, I|x; \alpha_1, \alpha_2, \beta, \gamma, \Sigma_\varepsilon, \Sigma_\eta, \Sigma_\mu) \\ = \int \prod_{\ell=1}^L \frac{1}{\sigma_{\eta_\ell}} \varphi\left(\frac{x_\ell^* - \beta'_\ell z_\ell}{\sigma_{\eta_\ell}}\right) \times \prod_{r=1}^R \frac{1}{\sigma_{\eta_r}} \varphi\left(\frac{I_r - \gamma'_r x^*}{\sigma_{\eta_r}}\right) \\ \times \frac{e^{\alpha'_{1i} x_i + \alpha'_{2i} x^*}}{\sum_{j \in I} e^{\alpha'_{1j} x_i + \alpha'_{2j} x^*}} dx^*. \end{aligned} \quad (8)$$

The assumption of standard normal distribution for the error term of the structural equation gives  $\eta_\ell = \sigma_{\eta_\ell} \tilde{\eta}_\ell$  so as  $\tilde{\eta}_\ell \sim N(0, 1)$ . This assumption converts Equations 8 and 9:

$$\begin{aligned} L(y, I|x; \alpha_1, \alpha_2, \beta, \gamma, \Sigma_\varepsilon, \Sigma_\eta, \Sigma_\mu) \\ = \int \prod_{\ell=1}^L \varphi(\tilde{\eta}_\ell) \times \prod_{r=1}^R \frac{1}{\sigma_{\eta_r}} \varphi\left(\frac{I_r - \gamma'_r (\beta'_\ell z_\ell + \sigma_{\eta_\ell} \tilde{\eta}_\ell)}{\sigma_{\eta_r}}\right) \\ \times \frac{e^{\alpha'_{1i} x_i + \alpha'_{2i} (\beta'_\ell z_\ell + \sigma_{\eta_\ell} \tilde{\eta}_\ell)}}{\sum_{j \in I} e^{\alpha'_{1j} x_i + \alpha'_{2j} (\beta'_\ell z_\ell + \sigma_{\eta_\ell} \tilde{\eta}_\ell)}} d\tilde{\eta}_\ell. \end{aligned} \quad (9)$$

By applying simulated maximum likelihood, the likelihood Equation 9 converts to Equation 10:

$$\begin{aligned} \tilde{L}(y, I|x; \alpha_1, \alpha_2, \beta, \gamma, \Sigma_\varepsilon, \Sigma_\eta, \Sigma_\mu) \\ = \frac{1}{\mathcal{M}} \sum_{m=1}^{\mathcal{M}} \left( \prod_{r=1}^R \frac{1}{\sigma_{\eta_r}} \varphi\left(\frac{I_r - \gamma'_r (\beta'_\ell z_\ell + \sigma_{\eta_\ell} \tilde{\eta}_\ell^m)}{\sigma_{\eta_r}}\right) \right) \\ \times \frac{e^{\alpha'_{1i} x_i + \alpha'_{2i} (\beta'_\ell z_\ell + \sigma_{\eta_\ell} \tilde{\eta}_\ell^m)}}{\sum_{j \in I} e^{\alpha'_{1j} x_i + \alpha'_{2j} (\beta'_\ell z_\ell + \sigma_{\eta_\ell} \tilde{\eta}_\ell^m)}}, \end{aligned} \quad (10)$$

where  $\mathcal{M}$  is the number of random draws from  $\tilde{\eta}_\ell$  for each observation that is denoted by  $\tilde{\eta}_\ell^m$ ,  $m \in \{1, 2, \dots, \mathcal{M}\}$ . According to Equation 11, the logarithm of the likelihood equation is maximized over the observations  $q \in \{1, 2, \dots, Q\}$  to determine the vectors of the parameters  $(\alpha_1, \alpha_2, \beta, \gamma, \Sigma_\varepsilon, \Sigma_\eta, \Sigma_\mu)$ :

$$\begin{aligned} \ln \tilde{L} \\ = \max_{\alpha_1, \alpha_2, \beta, \gamma, \Sigma_\varepsilon, \Sigma_\eta, \Sigma_\mu} \sum_{q=1}^Q \ln \tilde{L}(y_q, I_q|x_q; \alpha_{1q}, \alpha_{2q}, \beta_q, \gamma_q, \Sigma_{\varepsilon q}, \Sigma_{\eta q}, \Sigma_{\mu q}). \end{aligned} \quad (11)$$

## Data: RVS

The RVS is an online survey collected on 1,691 Americans by Qualtrics from March to June 2018. Figure 2 visualizes the locations of the individual respondents, most of whom live in the states of California, Illinois, Texas, New York, and New Jersey. The respondents, who represent their households, are asked four types of questions, including their socioeconomic characteristics, attributes of their households' existing vehicle(s), their attitudes and preferences, and dynamics of their households' characteristics

and vehicle decision making over the past 10 years from 2008 to 2017. This section presents a statistical analysis of the sample dataset.

### *Socioeconomic Characteristics*

A comparison between the statistical distribution of the dataset with the national values revealed that the dataset is twofold biased toward non-Hispanic two-member households living in urban areas without children, as well as individuals who are fully employed with higher education levels and who are middle-aged. To avoid biases associated with sampling and to have a robust database, the sample distribution was aligned with the population distribution at both household and individual levels (see Yeager et al. [38] for comparing weighted and unweighted estimates and Stuart [39] for a review on methods for matching sample and population). To do so, the method of ranking adjustment was applied to calculate the weight of each household and each individual using the American Community Survey 2013–2017 5-year data release (40). The weights were then used for model estimation.

At the household level, the weights were calculated for four household structure types (household sizes of one, two, three, and four or more), four child-based groups of households (no children, one child, two children, and three or more children), two ethnicity types (Hispanic and non-Hispanic), five race groups (White, Black or African/American, American Indian or Alaska native, Asian, and other), nine income levels, four groups of workers (zero, one worker, two workers, and three or more workers), four vehicle ownership levels (one vehicle, two vehicles, three vehicles, and four or more vehicles), and two residential regions (urbanized and unurbanized residence). At the individual level, the weights were calculated for two gender types (males and females), nine age categories, seven employment types, and five education levels. The unweighted and weighted socioeconomic characteristics are presented in Table 2.

### *Attitudes and Preferences*

The survey collects respondents' attitudes and preferences by asking their opinions about seven groups of statements. Four of these groups, which represent four attitudinal factors, ask about the individuals' attitudes toward vehicle decision making measured by a five-point Likert scale, ranging from 1 ("not at all important") to 5 ("very important"). These four attitudinal factors are labeled as attentiveness to vehicle cost, quality, and attributes, and social influence in vehicle decision making. Figure 3 shows the statistical distribution of the measurement indicators of the four attitudes, where each indicator represents one statement in the survey.

Three groups of statements in the survey determine the respondents' lifestyle preferences, which are measured by a five-point Likert scale, ranging from 1 ("strongly disagree") to 5 ("strongly agree"). These preferential factors are labeled as environmental consciousness, technology savviness, and pro-driving. Figure 4 shows the average values of the measurement indicators of these three preferential factors over the individual respondents, where each indicator represents one statement of the survey.

### *Dynamics of Household Attributes and Vehicle Decision Making*

The survey asks respondents about two sets of retrospective questions spanning a 10-year course of their household decisions from 2008 to 2017. One set determines the number of changes in three types of socioeconomic attributes that households have experienced: household structure, income level, and residential status. Figure 5 shows the values of these changes averaged over the sample of 1,691 respondents.

The second set of retrospective questions determines two vehicle decisions that households have made: vehicle transaction and fuel types. It was observed that 1,691 households have made 5,224 vehicle transaction and fuel type choices over the 10-year course. Clearly, this indicates that some households have had more than one vehicle transaction during this period. Figure 6 presents the timeline of these decisions and the associated share of each decision. These decisions are considered as the outcome variables of the ICLV model.

## **Results**

All seven latent constructs described in the previous section on data cannot enter the ICLV model to avoid possible correlations among the constructs. To select the constructs for the ICLV model estimation, we used confirmatory factor analysis, which connects the latent constructs to the corresponding indicators. According to the results presented in Table 3, Cronbach's alpha values and composite reliability coefficients of all seven constructs are above the threshold value of 0.7, which indicates the reliability of the constructs (41). The constructs with the larger shares of explained variance are then selected to enter the ICLV model, which include social influence in vehicle decision making, environmental consciousness, attentiveness to vehicle attributes, and technology savviness, with the explained variance values equal to 18.27%, 15.26%, 10.67%, and 9.44%, respectively.

The ICLV model is then estimated, given these four latent constructs and the set of exogenous variables. The estimation results are discussed in the three subsections below, including measurement equations, structural

**Table 2.** Statistical Distribution of Socioeconomic Characteristics (Sample Size = 1,691 Respondents)

Variables	Unweighted share (%)	Weighted share (%)	Variables	Unweighted share (%)	Weighted share (%)
<b>Household level</b>			<b>Individual level</b>		
Household size			Gender		
1	22.89	23.07	Male	48.91	53.29
2	44.71	34.51	Female	51.09	46.71
3	16.09	16.67	Age (years)		
4 +	16.32	25.75	16–17	0.65	4.38
# children			18–24	7.39	12.04
0	73.27	58.37	25–34	17.33	17.48
1	13.60	17.92	35–44	14.84	15.95
2	9.23	15.52	45–54	13.72	17.24
3 +	3.90	8.20	55–64	20.82	15.84
Ethnicity			65–74	20.82	9.88
Hispanic or Latino	9.76	17.24	75–84	4.02	4.90
Non-Hispanic	90.24	82.76	≥ 85	0.41	2.28
Race			Employment status		
White	73.74	73.05	Full-time	49.32	40.05
Black or African/ American	10.29	12.64	Part-time	9.88	8.82
American Indian or Alaska native	0.83	0.81	Self-employed	7.39	5.04
Asian	6.21	5.35	Unpaid volunteer or intern	0.65	0.52
Other	8.93	8.15	Homemaker	4.32	27.43
Income			Retired	25.07	13.43
<\$10K	2.48	6.66	Not currently employed	3.37	4.71
\$10K–\$24K	5.14	14.67	Education level		
\$25K–\$34K	5.44	9.53	Less than high school	0.77	12.78
\$35K–\$49K	8.99	12.86	High school graduate	9.99	27.72
\$50K–\$74K	15.85	17.69	Some college/ technical training/ associate degree	27.26	31.15
\$75K–\$99K	17.80	12.36	Bachelor's degree	34.00	18.04
\$100K–\$149K	20.64	14.07	Graduate/postgraduate degree	27.97	10.31
\$150K–\$199K	10.29	5.77			
≥ \$200K	13.36	6.38			
# vehicles					
1	35.01	36.00			
2	43.58	41.19			
3	13.25	15.76			
4	8.16	7.06			
Region					
Urbanized	86.64	78.92			
Unurbanized	13.36	21.08			

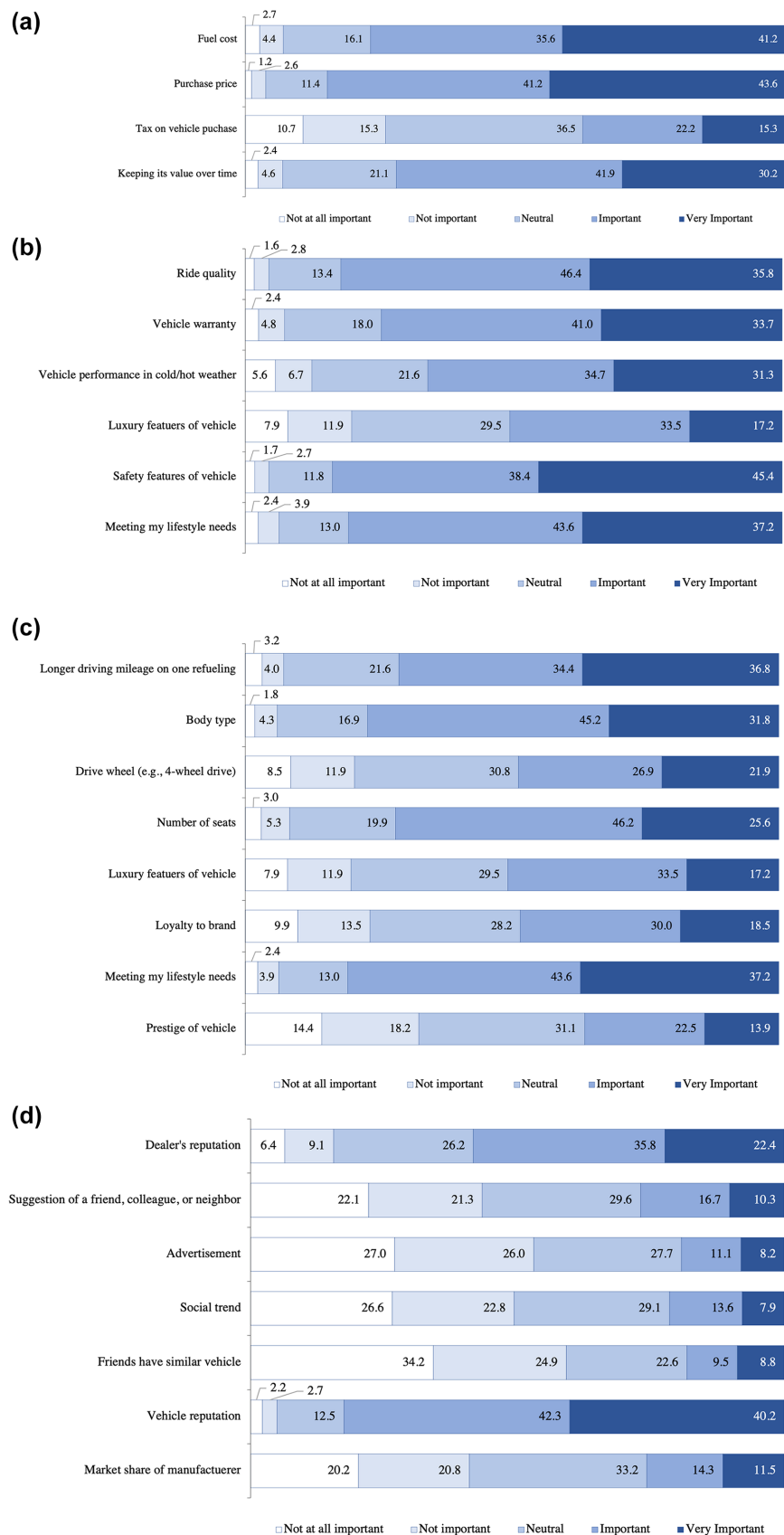
equations, and the choice model, followed by the sensitivity analysis of the results. Almost all model parameters are statistically significant at a 95% confidence interval, and the model has an overall acceptable goodness of fit.

### Measurement Equations

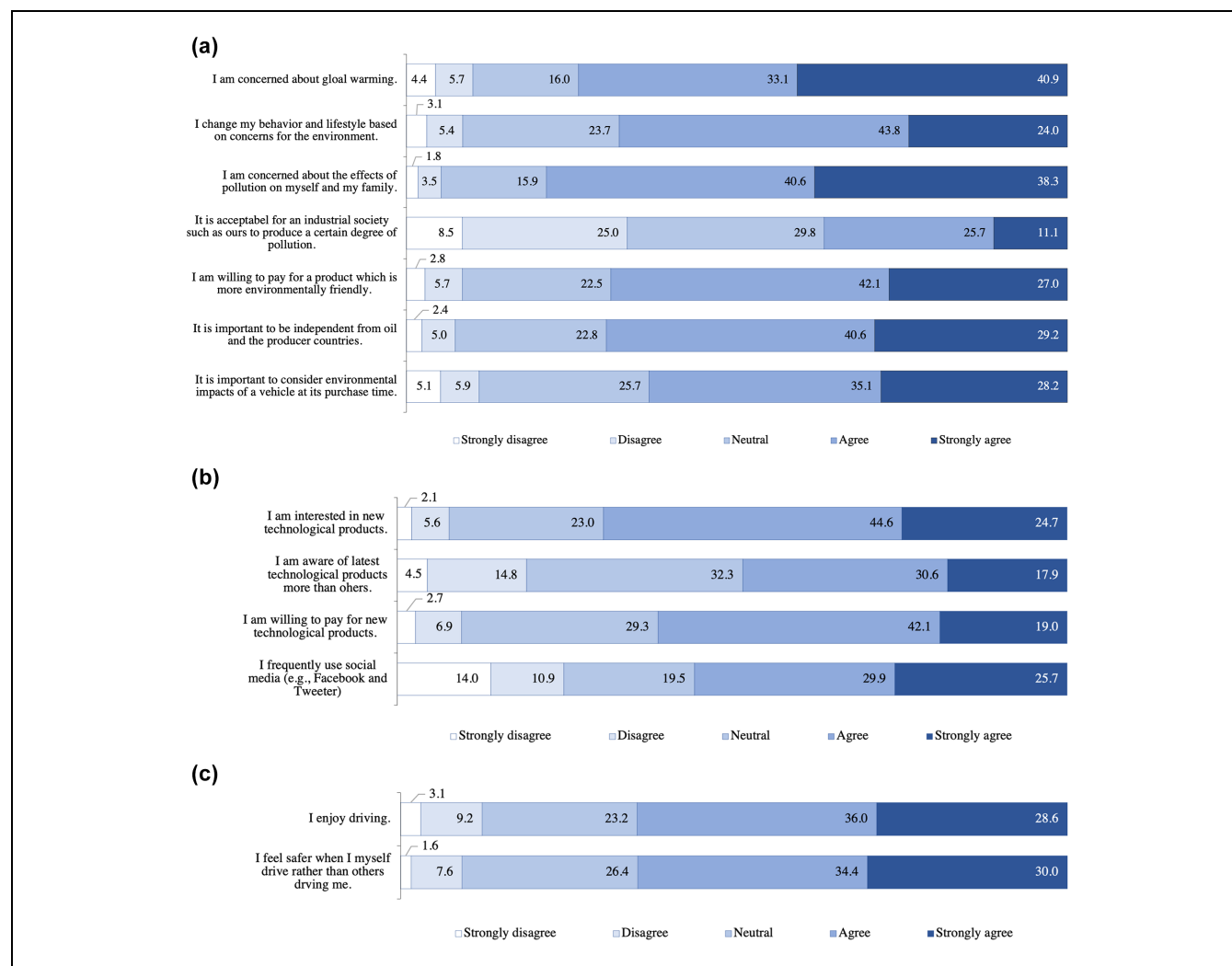
The estimation results of the measurement equations are presented in Table 4, which delineates the weights of the

latent constructs on the measurement indicators. The latent construct on vehicle attribute attentiveness measures the individuals' and their households' attention to various vehicle attributes at the time they make vehicle decisions. The estimated coefficients indicate that this latent construct contributes more to the weights on indicators related to nonoperational attributes (i.e., prestige of vehicle, loyalty to brand, and luxury features of vehicle in descending order) than operational/physical attributes (i.e., drive wheel, number of seats, body type, and safety





**Figure 3.** Average values of statements measuring attitudes toward vehicle decision making, including: (a) vehicle cost attentiveness, (b) vehicle quality attentiveness, (c) vehicle attributes attentiveness, and (d) social influence in vehicle decision making in percentage (sample size = 1,691 respondents).



**Figure 4.** Average values of statements measuring lifestyle preference, including: (a) environmental consciousness, (b) technology savviness, and (c) pro-driving in percentage (sample size = 1,691 respondents).

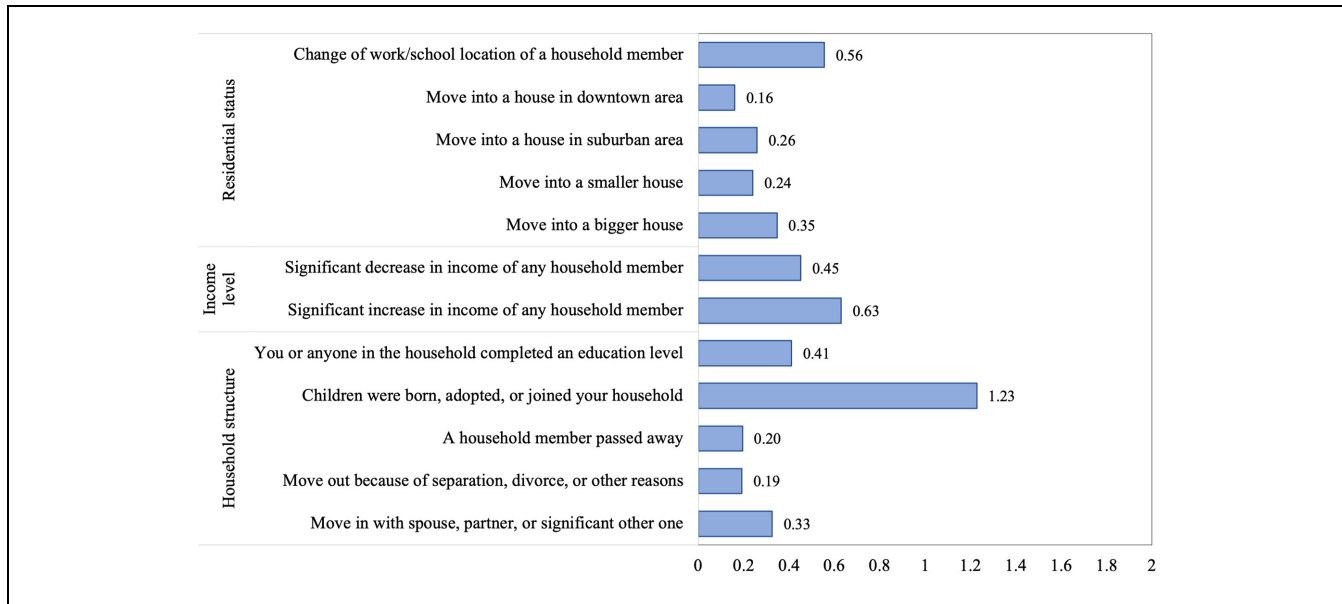
features of a vehicle in descending order). Turning to the latent variable on social influence, it explains how the individuals' and their households' vehicle decision making is influenced by their social environment, such as friends, colleagues, neighbors, and advertisements. As per the results, this latent construct has greater impacts in descending order on the indicators measuring advertisements, social trend, and friends having a similar vehicle.

The latent construct on environmental consciousness is found mostly to influence the individuals' opinions on changing behavior and lifestyle and being concerned about the effects of pollution, as indicated by their slightly larger coefficients compared with other indicators. Finally, the latent construct explaining individuals' technology savviness has a more tangible influence in descending order on their awareness of technological products, willingness to pay for technological products,

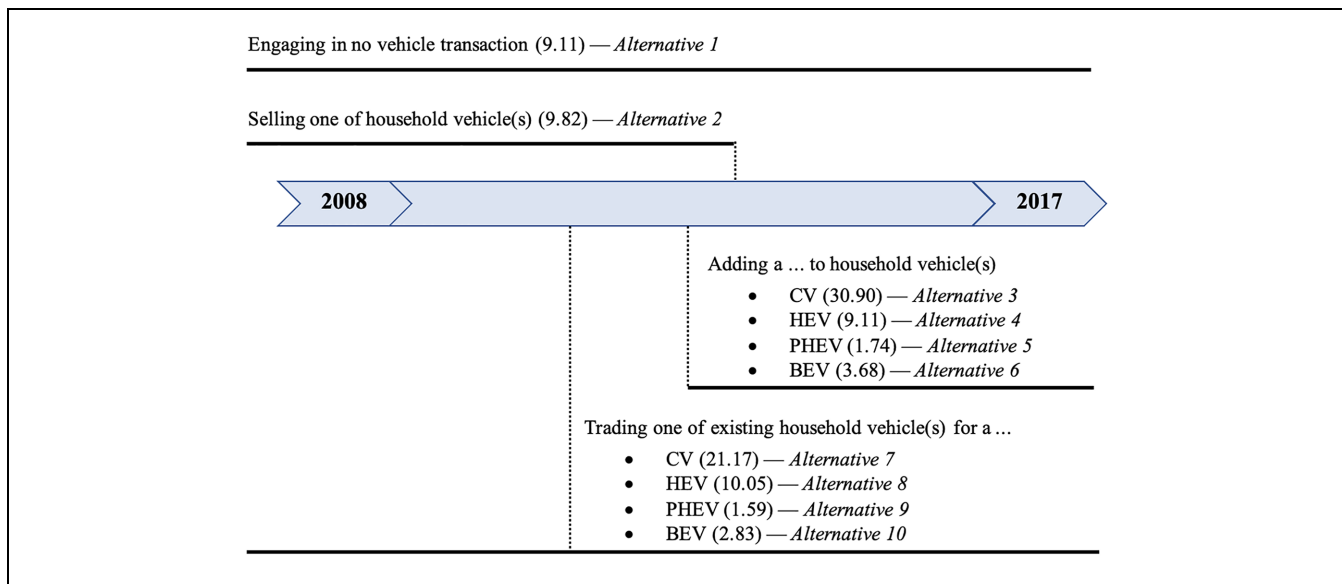
and interest in new technological products than on their social media usage frequency.

### Structural Equations

The estimation results of the structural equations signify a set of five socioeconomic characteristics (Table 5). Gender appears as a dummy variable, taking 1 for females. The negative signs of this variable in the equations of the four latent constructs mean that, compared with males, females are likely less vehicle attribute attentive, socially influenced, environmentally conscious, and technology savvy. Age appears as two dummy variables, revealing the nonlinear aging effect. One variable takes 1 for young individuals and 0 otherwise. The other variable takes 1 for the elderly and 0 otherwise. The results reveal that young individuals, in contrast to the elderly, likely pay more attention to vehicle attributes, are influenced



**Figure 5.** History of household socioeconomic attributes over the past 10 years (average values on the sample dataset with size 1,691 respondents).



**Figure 6.** History of household fuel type and vehicle transaction decisions (note: numbers in parentheses show shares of each decision considering the total 5,224 decisions, and endpoints of solid line segments show vehicle transaction events).

by social factors, and are technology savvy. Moreover, young individuals are probably more conscious of environmental issues than other age groups.

Education is statistically significant as a dummy variable, taking 1 for those who are highly educated, namely, with a bachelor's degree or higher. The highly educated individuals are likely more conscious of environmental issues and technology savvy than others, whereas they are less attentive to vehicle attributes and less socially influenced. Employment status is found to be significant

as a dummy variable, taking 1 for those who are paid employees and 0 otherwise. The results show that paid employees pay more attention to vehicle attributes and are more influenced by social factors than others.

Household structure appears in the model by a dummy variable, taking 1 for those who live alone and 0 otherwise. People who live alone, rather than with others, are likely less attentive to vehicle attributes, while they are positively affected by their social environment.

**Table 3.** Estimation Results of the Confirmatory Factor Analysis

Indicators	Loading	t-Stat	Cronbach's alpha value	Composite reliability
Attitudes toward vehicle decision making				
Indicators of vehicle cost attentiveness	na	na	0.85	0.87
My household considers ... in vehicle decision making				
Fuel cost	0.563	24.04	na	na
Purchase price	0.389	12.10	na	na
Tax on vehicle purchase	0.439	15.63	na	na
Keeping its value over time	0.577	27.72	na	na
Indicators of vehicle quality attentiveness	na	na	0.84	0.88
My household considers ... in vehicle decision making				
Ride quality	0.681	29.78	na	na
Vehicle warranty	0.556	28.70	na	na
Vehicle performance in cold or hot weather	0.569	22.20	na	na
Luxury features of vehicle	0.614	22.23	na	na
Safety features of vehicle	0.678	25.32	na	na
Meeting my lifestyle needs	0.537	21.28	na	na
Indicators of vehicle attributes attentiveness	na	na	0.91	0.92
My household considers ... in vehicle decision making				
Luxury features of vehicle	0.596	30.50	na	na
Safety features of vehicle	0.655	27.87	na	na
Body type	0.360	14.24	na	na
Drive wheel (e.g., two-wheel drive)	0.536	26.15	na	na
Number of seats	0.394	16.97	na	na
Loyalty to brand	0.663	37.45	na	na
Prestige of vehicle	0.713	44.37	na	na
Indicators of social influence	na	na	0.89	0.92
My household considers ... in vehicle decision making				
Dealer's reputation	0.471	25.47	na	na
Suggestion of a friend, colleague, or neighbor	0.756	58.94	na	na
Advertisement	0.843	92.12	na	na
Social trend	0.810	72.10	na	na
Friends have similar vehicle	0.775	69.87	na	na
Vehicle reputation	0.249	11.25	na	na
Market share of manufacturer	0.751	55.17	na	na
Lifestyle preference				
Indicators of environmental consciousness	na	na	0.88	0.89
I am concerned about global warming	0.693	38.49	na	na
I change my behavior and lifestyle based on concerns about the environment	0.743	40.23	na	na
I am concerned about the effects of pollution on myself and my family	0.748	50.54	na	na
I am willing to pay for a product that is more environmentally friendly	0.698	35.59	na	na
It is important to be independent from oil and the producer countries	0.603	27.07	na	na
It is important to consider environmental impacts of a vehicle at its purchase time	0.622	27.42	na	na
Indicators of technology savviness	na	na	0.91	0.93
I am interested in new technological products	0.668	32.33	na	na
I am aware of latest technological products more than others	0.766	44.76	na	na
I am willing to pay for new technological products	0.724	40.36	na	na
I frequently use social media (e.g., Facebook, Tweeter, Instagram)	0.439	16.78	na	na
Indicators of pro-driving	na	na	0.87	0.89
I enjoy driving	0.703	16.51	na	na
I feel safer when I drive rather than when others drive me	0.492	12.77	na	na

Note: na = not applicable.

**Table 4.** Estimation Results of the Measurement Equations

Indicators	Coefficient	t-Stat
Indicators of vehicle attribute attentiveness		
My household considers ... in vehicle decision making		
Luxury features of vehicle	0.60	30.85
Safety features of vehicle	0.34	13.46
Body type	0.36	13.85
Drive wheel (e.g., two-wheel drive)	0.51	24.09
Number of seats	0.40	17.17
Loyalty to brand	0.66	36.91
Prestige of vehicle	0.72	44.12
Indicators of social influence		
My household considers ... in vehicle decision making		
Dealer's reputation	0.46	23.08
Suggestion of a friend, colleague, or neighbor	0.73	49.78
Advertisement	0.83	81.57
Social trend	0.79	60.75
Friends have similar vehicle	0.75	59.46
Vehicle reputation	0.24	10.48
Market share of manufacturer	0.74	50.04
Indicators of environmental consciousness		
I am concerned about global warming	0.71	41.55
I change my behavior and lifestyle based on concerns about the environment	0.76	43.03
I am concerned about the effects of pollution on myself and my family	0.75	50.67
I am willing to pay for a product which is more environmentally friendly	0.71	36.86
It is important to be independent from oil and the producer countries	0.61	27.30
It is important to consider environmental impacts of a vehicle at its purchase time	0.62	27.79
Indicators of technology savviness		
I am interested in new technological products	0.68	34.78
I am aware of latest technological products more than others	0.81	57.38
I am willing to pay for new technological products	0.70	38.66
I frequently use social media (e.g., Facebook, Tweeter, and Instagram)	0.43	17.06

**Table 5.** Estimation Results of the Structural Equations

Exogenous variables	Vehicle attribute attentiveness		Social influence		Environmental consciousness		Technology savviness	
	Coef.	t-Stat	Coef.	t-Stat	Coef.	t-Stat	Coef.	t-Stat
Socioeconomic characteristics								
Gender								
Female	-0.14	-4.99	-0.15	-6.41	-0.11	-4.05	-0.31	-12.46
Age (years)								
Young (18–34)	0.12	3.87	0.33	13.35	0.16	6.75	0.19	7.54
Elderly ( $\geq 65$ )	-0.12	-4.82	-0.14	-6.44			-0.16	-6.67
Education level								
Bachelor's degree or higher	-0.09	-3.11	-0.05	-2.08	0.11	4.38	0.12	4.81
Employment status								
Paid employed	0.21	6.35	0.12	4.84	ns	ns	ns	ns
Household structure								
Living alone	-0.07	-2.68	0.05	2.39	ns	ns	ns	ns

Note: ns = not significant.

### Choice Model

The estimation results of the MNL choice model are presented in Table 6. It is worth noting that in the sample dataset used for the model estimation, the summation of observations across vehicle transaction types, except for

the sell alternative, yields the number of existing household vehicles. Across the existing vehicle sample, the distribution of four vehicle fuel types, including CV, HEV, PHEV, and BEV, are, respectively, 66.38%, 22.71%, 3.69%, and 7.22%. A comparison of these values with

**Table 6.** Estimation Results of the Choice Model

Explanatory variables	Sell			Add						Trade														
	CV			HEV			PHEV			BEV			CV			HEV			PHEV			BEV		
	Coef.	t-Stat		Coef.	t-Stat		Coef.	t-Stat		Coef.	t-Stat		Coef.	t-Stat		Coef.	t-Stat		Coef.	t-Stat		Coef.	t-Stat	
Constant	-0.23	-4.43	ns	ns	-4.09	-10.32	-6.63	-17.84	-6.63	-14.08	ns	ns	-4.09	-5.55	-6.63	-17.86	-6.63	-16.82						
Vehicle attributes																								
Ownership type																								
Lease vehicle	ns	ns	1.46	5.93	1.70	6.21	1.23	2.89	1.76	5.88	2.11	8.51	1.56	5.52	3.34	10.20	3.14	10.51						
Socioeconomic characteristics																								
Race																								
Asian	ns	ns	ns	ns	0.30	2.02	ns	ns	0.41	2.07	ns	ns	ns	ns	ns	ns	0.59	2.35						
Ethnicity																								
Hispanic or Latino	ns	ns	0.29	3.93	0.45	3.97	ns	ns	0.63	4.10	ns	ns	ns	ns	ns	ns	ns	ns						
Part of household income is gained by vehicle																								
Yes	ns	ns	0.18	2.33	0.52	4.56	0.73	3.35	0.59	3.90	ns	ns	0.29	2.45	0.57	2.45	0.83	4.58						
History of household socioeconomic characteristics																								
Change of household structure																								
# children joining	ns	ns	0.51	17.62	0.37	5.07	ns	ns	0.36	3.48	ns	ns	ns	ns	ns	ns	ns	ns						
Change of income level																								
# increases	ns	ns	0.14	4.42	0.08	1.78	0.34	5.56	0.19	3.43	0.22	7.02	ns	ns	ns	ns	0.14	1.85						
# decreases	0.17	4.38	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns						
Change of residential status																								
# moves to suburban	ns	ns	ns	ns	ns	ns	0.75	5.68	0.42	3.88	0.16	2.70	0.24	2.75	ns	ns	ns	ns						
Latent constructs																								
Vehicle attribute attentiveness	ns	ns	ns	ns	-0.60	-2.66	ns	ns	-2.13	-6.12	0.74	9.26	-0.63	-3.04	ns	ns	ns	ns						
Social influence	ns	ns	0.33	9.54	0.54	5.90	0.65	6.40	1.38	9.64	ns	ns	0.17	1.93	ns	ns	ns	ns						
Environmental consciousness	0.25	4.22	ns	ns	0.22	2.61	ns	ns	ns	ns	ns	ns	0.57	8.22	0.58	3.56	0.50	3.02						
Technology savviness	ns	ns	ns	ns	0.25	2.67	ns	ns	0.52	4.32	ns	ns	ns	ns	ns	ns	0.32	2.01						

Note: CV = conventional vehicle; HEV = hybrid electric vehicle; PHEV = plug-in hybrid electric vehicle; BEV = battery electric vehicle; ns = not significant. The base alternative is no transaction. Number of observations = 5,224 transaction and fuel type decisions; log likelihood at zero = -15,503.59; log likelihood with constants = -13,404.54; log likelihood at convergence = -12,391.18.

the existing market shares of vehicle fuel types (10, 42, 43) reveals that the three EV types (i.e., HEV, PHEV, and BEV) are oversampled. To avoid biases, we applied the method suggested by Cherchi and de Dios Ortúzar (44) by adjusting the constant terms so that the model with only constant terms gives the market share. The rest of the section discusses the estimation results.

**Vehicle Attributes.** Vehicle ownership type is found to be statistically significant as a dummy variable, taking 1 for lease vehicles. The results show that the individuals are likely interested in trading an existing household vehicle for a lease vehicle and adding a lease vehicle to their households' existing vehicle(s), with a higher tendency toward the former. In particular, the largest coefficients of this variable belong to traded-for PHEV and BEV, indicating the greater tendency of individuals toward trading their vehicle(s) for lease PEV, especially PHEV. Given the lower acquisition cost of lease vehicles versus the higher purchase price of PEV, it can be inferred that the high purchase price may impede the owned PEV adoption, which can be of interest to policy decision makers. This is generally consistent with the findings of the prior studies, which find vehicle leasing the most preferred option for BEV (22) and also the interest of lease vehicle users in BEV adoption (25).

**Socioeconomic Characteristics.** Race appears in the model as a dummy variable, taking 1 for Asians. The results reveal the positive signs of this variable in the utility equations of added and traded-for BEV as well as added HEV. This suggests the positive tendency of Asians toward BEV, especially as a traded-for vehicle, in addition to their interest in adding a HEV to their household vehicle(s). Ethnicity is also found to be significant in the model as a dummy variable, taking 1 for Hispanic or Latino individuals. The positive signs of this variable in the utility equations of added BEV, HEV, and CV in descending order of magnitude indicate the higher tendency of Hispanic or Latino individuals toward these alternatives than other ethnic groups.

The variable representing whether an individual's household uses its vehicle to gain part of its income appears as a dummy variable, taking 1 for those who responded yes to this question. The results show that those with a positive answer to this question have a greater proclivity toward adding or trading in a vehicle. Moreover, their preferred fuel types for both added and traded-for vehicles are BEV and PHEV.

**History of Household Socioeconomic Characteristics.** The estimated model includes three groups of variables describing dynamics of the socioeconomic characteristics of the

individuals' households over the past 10 years from 2008 to 2017. The first group captures the change of household structure with regard to the number of children joining the households. The results indicate that more children joining a household translates intuitively into more inclination toward adding CV, HEV, and BEV in descending order, given the corresponding positive coefficients.

The second group captures the change of household income over the past 10 years by two variables measuring the number of times the households' income increases or decreases. The results indicate that an increase in income level leads to higher interest in adding a vehicle, regardless of the fuel type, and trading in a vehicle, especially CV and BEV. In contrast, more instances of a drop in income level increase the probability of selling a vehicle compared with the other transaction types.

The last group describes the change of household residential status over the past 10 years through a variable measuring the number of times a household moves to suburban areas. This variable appears with positive signs in the utility equations of added PEV as well as traded-for HEV and CV. This suggests that moving to suburban areas increases the probability of acquiring PHEV and BEV, with a higher tendency toward PHEV. This might be because of the limitation of installing PEV charging infrastructure at residences in downtown compared with suburban areas. Therefore, it can be inferred that a major determinant of EV adoption behavior is provision of charging infrastructure, which is of note to policy decision makers, as also corroborated by similar findings of the previous studies reviewed in Li et al. (6), which detects charging infrastructure as a crucial barrier to PEV adoption. The results further show that relocating to suburban areas encourages trading an existing household vehicle for CV and HEV, although with less tendencies than those of acquiring PHEV and BEV.

**Latent Constructs.** The latent construct explaining vehicle attribute attentiveness appears with negative signs in the utility equations of added BEV as well as traded-for and added HEV in descending order. This signifies that people attentive to vehicle attributes less likely opt for acquiring BEV as an added vehicle to their household vehicle(s) and HEV. In contrast, they are likely attracted to traded-for CV more than other options, given the positive sign of its coefficient in the associated utility equation. This finding can be justified by noting that BEV and HEV have limited attributes compared with CV, which may negatively affect BEV and HEV attractiveness. However, BEV uptake can be expected to increase gradually as BEV attributes advance, particularly by the entrance of more prominent car manufacturers into the BEV market that could enhance nonoperational attributes (e.g., prestige of vehicle and luxury features of

vehicle), which were found in the estimated measurement equations (Table 4) to be more noted by vehicle attribute attentive individuals than operational attributes of a vehicle (e.g., drive wheel and body type).

The latent factor reflecting the role of social influence on vehicle decision making appears in the utility equations of all types of added vehicles and traded-for HEV. In particular, those who are more influenced by their social environment are more likely to add a vehicle to their existing household vehicles, especially adding PEV, with more inclination toward BEV than PHEV. Socially influenced individuals are also interested in trading in a HEV, yet with a lower tendency than adding a vehicle to the existing household vehicles. This finding is consistent with previous studies. Kim et al. (45) found that EV adoption behavior is affected by positive public opinion about EVs, especially when the EV market share is almost half of friends in people's social network. Bansal et al. (23) found that social influence likely affects EV early adopters, who believe in its positive environmental effects. To promote BEV uptake, incentivizing policies can thus focus on the cohort of socially influenced people, noting that such individuals tend more to consider advertisement and social trend when making a vehicle decision, as per the estimated measurement equations (Table 4).

When it comes to the latent environmental consciousness construct, it appears with positive signs in the utility equations of the three traded-for EV types (i.e., HEV, PHEV, and BEV), added HEV, and selling a vehicle in descending magnitudes. This suggests that environmentally conscious people are more interested in traded-for EV—rather than added EV—with close tendencies toward the three EV types, while their next preferred options are selling an existing household vehicle and acquiring HEV. This finding is in line with prior studies. For example, Jensen et al. (46) found that individuals' interests in EVs are positively affected by higher environmental concern, where their concern does not change with EV experience. Kim et al. (45) also reported a similar positive effect of environmental concerns on EV adoption. These findings, as an expected behavior of environmentally conscious people, can be leveraged to devise policies for promoting EV adoption by trading an existing vehicle for an EV. Such policies can be geared toward drawing individuals' and communities' attention to the harmful consequences of CV to stimulate their environmental consciousness, which would likely translate into changing behavior and lifestyle, as suggested by the estimated measurement equations (Table 4).

The positive signs of the latent construct explaining technology savviness in the utility functions of BEV alternatives indicate the positive tendency of technology savvy persons toward BEV, especially as an added vehicle to

the existing household vehicles. This cohort of individuals is also interested in adding HEV to their existing vehicles, yet to a lesser degree than adding BEV. Recalling from the estimation results of the measurement equations that technology savvy individuals have greater awareness about, interest in, and willingness to pay for technological products than others, the findings of the choice model reveal that concentrating policy recommendations on raising awareness about technological aspect of EVs can result in pursuance of BEV adoption. It should be noted, however, that those who are technology savvy are more inclined toward adding BEV to the existing household vehicles than trading an existing vehicle for BEV, which might have implications for vehicle use and road congestion. Similarly, Kim et al. (45) report the tendency of those who are tech savvy toward EVs.

### Direct Elasticities

To analyze the estimated ICLV model further, we computed the direct elasticity of each choice alternative with respect to the explanatory variables (Equations 12 and 13), which is defined as the percentage change in the choice probability of the alternative caused by a percentage change in the desired explanatory variable while keeping all other explanatory variables constant (47):

$$Elasticity_{x_i} = \frac{1}{Q} \sum_{q=1}^Q (1 - f_{3i}^q) \alpha_{1i} x_i^q \quad (12)$$

$$Elasticity_{x_i^*} = \frac{1}{Q} \sum_{q=1}^Q (1 - f_{3i}^q) \alpha_{2i} x_i^{*q}. \quad (13)$$

Table 7 presents the calculated direct elasticities, indicating the inelasticity of all alternatives with respect to the explanatory variables. The largest elasticities belong to added BEV with respect to two latent constructs. Specifically, a 1% increase in the latent constructs explaining vehicle attribute attentiveness and social influence would decrease and increase the probability of adding a BEV to the existing household vehicle(s) by 0.71% and 0.65%, respectively. From a policymaking perspective, these findings clearly suggest that the most effective factor to consider for devising policies aimed at promoting BEV adoption is the social influence latent construct.

### Policy Implications

The findings from the estimated ICLV presented here could both support and complement the existing policies that aim to promote EV adoption. On the one hand, most existing policies launched globally provide financial incentives (e.g., EV purchase subsidies and tax exemptions) and nonfinancial incentives (e.g., charging



**Table 7.** Elasticity of Explanatory Variables of the ICLV Model

Explanatory variables	Sell Sell	Add				Trade			
		CV	HEV	PHEV	BEV	CV	HEV	PHEV	BEV
Vehicle attributes									
Ownership type									
Lease vehicle	ns	0.05	0.11	0.08	0.12	0.08	0.10	0.22	0.21
Socioeconomic characteristics									
Race									
Asian	ns	ns	0.03	ns	0.04	ns	ns	ns	0.05
Ethnicity									
Hispanic or Latino	ns	0.01	0.05	ns	0.07	ns	ns	ns	ns
Part of income is gained by vehicle									
Yes	ns	0.02	0.12	0.17	0.14	ns	0.07	0.13	0.19
History of household socioeconomic characteristics									
Change of household structure									
# children joining	ns	0.35	0.47	ns	0.46	ns	ns	ns	ns
Change of income level									
# increases	ns	0.05	0.06	0.25	0.14	0.11	ns	ns	0.10
# decreases	0.07	ns	ns	ns	ns	ns	ns	ns	ns
Change of residential status									
# moves to suburban	ns	ns	ns	0.23	0.13	0.04	0.08	ns	ns
Latent constructs									
Vehicle attribute attentiveness	ns	ns	−0.20	ns	−0.71	0.18	−0.21	ns	ns
Social influence	ns	0.06	0.25	0.31	0.65	ns	0.08	ns	ns
Environmental consciousness	0.04	ns	0.04	ns	ns	ns	0.10	0.10	0.09
Technology savviness	ns	ns	−0.004	ns	−0.007	ns	ns	ns	−0.004

Note: ICLV = integrated choice model with latent variables; CV = conventional vehicle; HEV = hybrid electric vehicle; PHEV = plug-in hybrid electric vehicle; BEV = battery electric vehicle; ns = not significant.

infrastructure provision) (24, 48). The effectiveness of these policies is implicitly corroborated by our findings related to explanatory variables representing the EV ownership type—which implies that higher purchase price hinders EV adoption—and the dynamics of households' residential status—which suggests that access to charging infrastructure hampers EV adoption.

On the other hand, the findings could provide insights into further complementing the existing policies that incentivize EV adoption. Specifically, most existing policies launched globally are generally based on a one-size-fits-all approach, which may not be equally effective to promote EV adoption across (1) distinct EV types (i.e., HEV versus PHEV versus BEV), (2) distinct vehicle transaction types leading to EV adoption (e.g., trading an existing household vehicle for an EV versus adding an EV to existing vehicles which might increase vehicle use and road congestion), and (3) distinct consumers with heterogeneous socioeconomic and latent attitudinal profiles. For instance, the highest return on incentivizing policy investments can be gained by specifically focusing on the socially influenced consumer profile (i.e., those who tend more to consider advertisement and social trend when making a vehicle decision) rather than other cohorts of consumers. However, such policies should be

carefully devised, since they will more likely lead to adding an EV—with more tendency toward BEV than other EV types—to the existing household vehicles, which might translate into higher levels of car ownership, car use, and traffic congestion.

## Conclusions

The present study contributes to the plethora of research on the consumer adoption behavior of EVs by modeling two intertwined dimensions of households' (as the decision-making unit) vehicle decision making: (1) vehicle fuel type, including fossil- CVs, HEV, PHEV, and BEV, and (2) vehicle transaction type, including no transaction, sell, add, and trade. To this end, an ICLV is presented to model vehicle transaction and fuel type choice simultaneously from a 10 alternative set of (1) engaging in no vehicle transaction; (2) selling one of the existing household vehicle(s), (3–6) adding a CV, HEV, PHEV, or BEV to household vehicle(s); and (7–10) trading one of household vehicle(s) for a CV, HEV, PHEV, or BEV. To estimate the ICLV model, this study further contributes to the EV adoption behavior literature by collecting a one-of-a-kind RP RVS in the United States in 2018, which asked 1,691 American households about

their vehicle decision making and historical changes of socioeconomic attributes over the past 10 years as well as their attitudes and preferences.

The model estimation results could help complement the existing globally launched EV adoption policies that are generally based on a one-size-fits-all approach, which may, however, not be equally effective in promoting EV adoption across distinct EV types (e.g., PHEV versus BEV), distinct vehicle transaction types leading to EV adoption (e.g., trading an existing household vehicle for an EV versus adding an EV to existing vehicles, which might increase vehicle use and road congestion), and distinct consumers with heterogeneous socioeconomic and latent attitudinal profiles. For instance, the highest return on incentivizing policy investments can be gained by specifically focusing on the socially influenced consumer profile (i.e., those who tend more to consider advertisement and social trend when making a vehicle decision) rather than other cohorts of consumers. However, such policies should be carefully devised, since they will more likely lead to adding an EV—with more tendency toward BEV than other EV types—to the existing household vehicles, which might translate into higher levels of car ownership, car use, and traffic congestion.

This study uses a sample dataset collected in 2018, which might miss changes in EV consumer behavior since then. To fill this gap, we suggest a future study on developing household vehicle decision-making models by collecting more recent datasets. The comparative analysis of such future studies with the findings of the current study can highlight the possible changes of consumers' behavior over time, which can also be noteworthy from a policymaking perspective.

### Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Fatemeh Nazari and Abolfazl Mohammadian; data collection: Fatemeh Nazari and Abolfazl Mohammadian; analysis and interpretation of results: Fatemeh Nazari and Mohamadhossein Noruzoliaee; draft manuscript preparation: Fatemeh Nazari and Mohamadhossein Noruzoliaee. All authors reviewed the results and approved the final version of the manuscript.

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