Applying Best–Worst Scaling to Assess Consumer Preferences for Electric Vehicles in Japan

by

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Abstract

The shift to electric vehicles (EV) is drawing attention globally. Widespread adoption of alternative-fuel vehicles may contribute to the alleviation of climate change and air pollution (Liao et al. 2017). In China, strong public policies have been implemented to promote new-energy vehicles to mitigate air pollution in urban areas. In Japan, although Nissan has sold a globally bestselling electric car called LEAF, the yearly sales of new 100% EVs were 0.4% in 2016. By contrast, the yearly sales of hybrid vehicles such as the PRIUS were 30.8% in the same year. Japanese consumers remain hesitant about purchasing EVs even though central and local governments offer subsidies and tax-exemption schemes to achieve alternative-fuel vehicle goals by 2030. Choice modelling approaches are useful for revealing consumer preferences for a new commodity. In this study, best–worst scaling (BWS) was applied to investigate consumer preferences for EVs. Although most Japanese consumers are unfamiliar with EVs, BWS can help obtain rich information and data on consumer preferences by identifying the "best" and "worst" options for each respondent. An online questionnaire survey was conducted in 2018, and 448 responses from Japanese consumers were collected. Both object case and multi-profile case BWS were applied in the survey. The results of the object case BWS revealed purchase price to be the most important factor in changing consumers' attitude toward EVs. In addition, the operation cost and driving range were similarly important. Conversely, it was demonstrated that CO_2 and air pollutant reduction were far less appealing. Multi-profile case BWS revealed that two different scenarios for operation cost, yen/100 km and annual saving, were both significant considerations when purchasing EVs. Random parameter logit estimates of both object case and multi-profile case BWS demonstrated the preference heterogeneity of every EV attribute. The results suggest that consumer preferences and purchase behaviors are diverse. Thus, more public programs that reduce the vehicle price and adequately disseminate the environmental advantages are necessary to promote the shift to EVs in Japan.

1 Introduction

In this study, Japanese consumer preferences for electric vehicles (EVs) were evaluated by applying two types of best–worst scaling (BWS) approaches to consider the future direction of a shift toward EVs in Japan. BWS is a type of stated-preference method that enables the assessment of the relative importance of and consumer preferences for multiple EV items. Whereas choice experiments take the form of choosing the best from multiple choices, BWS takes the form of choosing the best and the worst. The penetration of EVs in the Japanese market is still limited. These vehicles accounted for only 1% of the number of new-car sales in Japan in 2017. Many consumers are unfamiliar with EV characteristics. Therefore, stated-preference methods based on hypothetical scenarios were adopted to estimate consumer preferences. BWS makes it possible to obtain more information on the preferences of consumers who have not actually purchased EVs because it captures information on the most undesirable options as well.

There are a variety of EVs, such as hybrid electric vehicles (HEVs) and clean diesel vehicles (CDVs) among the next generation of cars. The major types of EVs being promoted by various programs include battery electric vehicles (BEVs), plug-in hybrid vehicles (PHEVs), and fuel cell vehicles (FCVs). The shift to EVs is being promoted by various programs such as the Zero Emission Vehicle (ZEV) program of the state of California, the Chinese government's New Energy Vehicle (NEV) policy, and CO_2 regulation in the EU. Under the ZEV and NEV initiatives, it is obligatory, within the state and country, respectively, for automobile companies to sell EVs at a certain rate. If they cannot achieve the target, a fine is imposed, and credits must be purchased from another automobile company. The share of emerging EV manufacturers, such as Tesla in the USA and BYD in China, are increasing. Global initiatives for CASE (Connected, Autonomous, Shared, Electric) pioneered by Daimler are being implemented by various players such as Apple, Waymo, and Uber, in addition to the existing major automobile companies.

The International Energy Agency global EV outlook 2018 (IEA 2018) provides a comprehensive look at the state and projection of EVs. The development of EVs aims at increasing energy security, improving air quality, reducing noise pollution, and reducing greenhouse gas emissions. EVs had record sales in 2017; over 1 million electric cars were sold with more than half of global sales in China. In terms of share, Norway was the most advanced market for electric car sales, with over 39% of new sales in 2017. Iceland follows at 11.7%, Sweden at 6.3%, China at 2.2%, Germany at 1.6%, the USA at 1.2%, and then Japan at 1.0%.

The EV shift and CASE are drawing a lot of attention in Asian countries. Widespread adoption of alternative-fuel vehicles (AFV) may contribute to the alleviation of climate change and air pollution (Liao et al. 2017). In China, strong public policies, such as subsidy and lottery waiver programs, have been implemented to promote new energy and zero emission vehicles to mitigate serious air pollution in urban areas. In Japan, the i-MiEV of Mitsubishi Motors was sold for corporate users in July 2009, and was sold as a mass-produced automobile in April 2010. Nissan's LEAF was launched in October 2010. Then, in Japan, the nuclear power plants stopped operating because of the severe accident at Fukushima Daiichi Nuclear Power Plant in March 2011. It seemed as if the business model of EVs that depended on cheap nighttime electric power had collapsed. However, after Volkswagen's exhaust gas fraud, which was discovered in 2015, the so-called “diesel-gate” incident, European automobile manufacturers are switching from diesel vehicles to EVs. In 2019, LEAF, sold by Nissan, had a cumulative sales volume of over 400,000 units globally and 100,000 units in Japan. The second-generation LEAF which was fully remodeled in September 2017 has a battery capacity of 40 kWh, and the catalog states that it can run for 400 km with full charge. EVs were 0.5% of new Japanese car sales in 2016, but this increased to 1% in 2017.

Choice modelling approaches are useful tools to reveal consumer preferences for a new commodity. Many case studies have applied choice experiments in the context of EVs and other next-generation models. Liao et al. (2017) conducted a comprehensive review of 26 choice modeling studies and considered the factors affecting consumer preferences. Nienhueser & Qiu (2016) demonstrated that willingness to pay (WTP) was higher in the USA when charging stations used renewable energies. Tanaka et al. (2014) demonstrated that government subsidies that lowered purchase prices also effectively increased Japanese and American consumers’ selection of EVs. Ito, Takeuchi & Managi (2018) estimated the WTP for a battery-switching system. Ito & Managi (2015) conducted a cost-benefit analysis of FCVs and EVs. Ito, Takeuchi & Managi (2013) conducted a WTP survey for improvements of facilities related to AFVs.

In this study, BWS is applied to investigate consumer preferences for EVs. Although most Japanese consumers are unfamiliar with EVs, BWS has certain advantages in obtaining rich information and data on consumer preferences by identifying the best and worst options for each respondent. Based on an online questionnaire survey, both object and multi-profile case BWS methods were applied in this study. Object case BWS can reveal the relative importance of EV characteristics. Multi-profile case BWS elicits marginal willingness to pay (MWTP) for each EV attribute. Two different scenarios for the operation cost of charging the EV’s battery installed were used for the multi-profile case BWS.

2 Methods

2-1 Best–Worst Scaling

The BWS is a relatively new analytical method formulated in the late 1980s, and officially reported in 1992 (Louviere, Flynn & Marley 2015). It has three categories: the object case (case 1), profile case (case 2), and multi-profile case (case 3). Although BWS is a type of choice modeling, it characteristically obtains the best and worst (or most and least) answers at the same time. This research applies two types of BWS, the object and multi-profile cases. These two BWS types ask about the respondent's preferences for specific EV characteristics.

Table 1: EV attributes/items for object case BWS

Attributes/Items	Details
Purchase price	Actual payment including subsidies and eco-car tax reduction
Operation cost	Cost for battery charging
Driving range	Maximum driving range of a fully charged battery
Charging availability	The number of charging stations for daily use
Charging time	The length of time for quick charge (outside) and normal charge (home)
Reduction of CO_2	More than 50% reduction of CO_2 emissions
Reduction of air pollutants	100% reduction of air pollutants
Driving performance	Equivalent acceleration, horsepower and torque, advanced control system
Battery life and warranty	Low deterioration, 8 years or 160,000 km warranty, roadside assistance

	Purchase price	Driving range	Reduction of CO_2
Most important	✔		
Least important			✔

Figure 1: Example of an object case best–worst question

2-2 Object case BWS

The object case BWS presents multiple questions for respondents, and encourages them to choose "best/most" and "worst/least" options. As shown in **Table 1**, nine items (attributes) which are characteristic of EVs were used with reference to Liao et al. (2017) and Tanaka et al. (2014): (1) purchase price; (2) operation cost; (3) driving range; (4) charging availability (infrastructure); (5) charging time; (6) reduction of CO_2; (7) reduction of air pollutants; (8) driving performance; and (9) battery life and warranty. Balanced incomplete block designs were applied for the above nine items. 12 choice sets were prepared, each comprising three items. These were presented to each respondent, with the form noted in **Figure 1**. They were presented in a set order such that they randomly changed when presented to each respondent.

Prior to the object case BWS questions in **Figure 1**, the following 12 warm-up questions were presented to give information on each item. The answer options for individual questions are: 1. quite influential, 2. influential, 3. somewhat influential, 4. not influential at all.

(Question)

"When comparing electric and conventional gasoline-powered vehicles, there are the following distinctive features: Please answer assuming scenes where you would consider buying an electric vehicle in the near future. When deciding whether you buy an electric vehicle or not, how much do you think the characteristics described in the following questions influence your decision?"

(1) The purchase price of electric vehicles is about several hundred thousand to 1.5 million yen higher than conventional gasoline vehicles.

(2) Government clean-energy subsidies, eco-car tax reduction, and local government subsidies at the time of purchase reduce the purchase price by 500,000 yen or more.

(3) For the same mileage, the electricity cost for charging will be cheaper than that of petrol. Electricity charges vary depending on conditions. However, as an example, if you are mainly using a quick charger, other than one in your home, and traveling 1,000 km a month (12,000 km a year), you will be able to save 5,000 yen a month (about 60,000 yen a year) compared with gasoline cars.

(4) The maximum driving distance after full charge is shorter than that of gasoline or hybrid vehicles. For example, the new Nissan LEAF catalog claims a 400 km driving distance. However, according to the US EPA standard, which is said to be closer to the actual mileage, approximately 240 km is possible.

(5) The available charging facility is installed in the parking place that you are using. In addition, if you have already built a house, you can install it at a budget of 20,000 to 100,000 yen.

For apartment houses that have already been built, 0.5 to 1.5 million yen is required for installation, and building consensus from residents is also required.

(6) When traveling, charging facilities are available in many places. Currently, charging facilities are being constructed all over the country. 7,100 quick-charging facilities and 20,000 normal-charging facilities have already been installed on highways, in convenience stores, shopping centers, road stations, and so on. There are approximately 31,000 gas stations nationwide. In conjunction with car navigation systems and smartphones, it is possible to find charging facilities for your destination quickly.

(7) The charging time for the car is approximately 40 minutes (approximately 80% of the full charge) with quick-charging equipment; it takes about 8 hours to fully charge the vehicle with normal-charging equipment. In addition, during a long-distance drive, you can prolong the driving distance by performing a short charge (10 to 20 minutes).

(8) The deterioration of the battery life is small, and the free repair guarantee in case of failure/malfunction is sufficiently substantial.

(9) Road-side assistance for "running out of charge" on the street corresponds to that for running out of gasoline. Drivers do not have to worry about long-distance drives.

(10) The vehicle is equipped with advanced automobile control technology for electric motors and superior driving performance; for example, its acceleration and power are equal to or better than that of gasoline cars.

(11) When renewable energy is used to charge an electric vehicle, greenhouse gas (such as CO_2) reduction of between 50 to 100% is achieved, which is effective for combating climate change.

(12) Because an electric vehicle runs with an electric motor only, discharge of air pollutants (nitrogen oxides, particulate matter, etc.) during driving is almost zero, thereby preventing air pollution.

2-3 Multi-profile case BWS

The multi-profile case BWS encourages respondents to choose the “best/most” and “worst/least” profiles. In normal choice experiments, respondents only choose the “best/most” option. Thus, only information on the “best/most” profile is obtained. The BWS is analytically advantageous, in that it obtains information on the best as well as the worst profiles. The orthogonal fractional factorial designs in the multi-profile case BWS allowed us to prepare 16 choice sets, each comprising four profile types with six attributes and four levels (**Table 2**). Respondents were presented with the form of the choice sets as noted in **Figure 2**. Each respondent was given eight different choice sets; these were divided into two groups. As the hypothetical scenario proposed by the BWS requires respondents (car drivers) to bear an additional financial burden to purchase an EV, the purchase price was established at up to an additional 1,250,000 yen, at 250,000-yen intervals.

Two hypothetical scenarios were prepared for the multi-profile case BWS, and comparative experiments were performed. The hypothetical scenarios differed in operation cost. For the multi-profile case BWS, hypothetical scenario A (electricity charge when driving 100 km) and hypothetical scenario B (fuel savings amount when driving for 10,000 km) are set for the electricity charge. As for the hypothetical scenarios, only A (electricity charge) and B (savings) were changed; the same sentences were used for the other scenarios. Prior to the choice set shown in **Figure 2**, the following sentences are presented. “There are four types of electric vehicles sold by the four automobile manufacturers. Which are the most attractive and the most unattractive vehicles when you consider buying? Please select one by one.”

Table 2: Attributes and levels

Attribute	Level 1	Level 2	Level 3	Level 4
Purchase price (plus thousand JPY)	500	750	1000	1250
A. Operation cost (JPY/100 km)	250	200	150	100
B. Operation cost (annual savings amount, thousand JPY)	40	60	80	100
Driving range	200	300	400	500
Charging availability of quick charge stations (% of existing gas stations)	25	50	75	100
Charging time (minutes, quick)	5	10	20	40

	Car A	Car B	Car C	Car D
Purchase price (plus thousand JPY)	+ 750	+1250	+1250	+1000
A. Operation cost (JPY/100 km)	200	100	250	100
B. Operation cost (annual saving, thousand JPY)	60	100	40	100
Driving range	300 km	500 km	400 km	200 km
Charging availability of quick charge station (% of existing gas stations)	50%	100%	50%	75%
Charging time (minutes, quick)	5	5	40	10
I am most likely to choose	✔			
I am least likely to choose			✔	

Figure 2: Example of a multi-profile case best–worst question with Scenarios A & B

(Question)

“Please imagine yourself thinking about purchasing an electric vehicle. Purchase price, electricity charging fee (operation cost), maximum driving distance, availability of quick charge facilities, and time required for quick charging are different.”

(1) “Purchase price” is the actual purchase price (thousands of yen higher than the gasoline-powered equivalent) after subtracting the government/local government subsidy and eco-car tax reduction from the manufacturer selling price. Because purchase choice varies from person to person, it is a price setting that thousands of yen is higher if the power source is electric, compared with the gasoline-powered equivalent to the car you are going to purchase.

(2A) “Operation cost” is a standard electricity cost for driving 100 km.

(2B) “Operation cost” shows how much electricity costs when driving 10,000 km per year, which is the average mileage, and can save thousands of yen compared with gasoline-powered vehicles.

(3) “Driving distance” is not the numerical value in the catalog, but is the average driving distance after full charge in a situation close to actual driving such as using the air conditioning.

(4) “Charging availability” means how many quick charging facilities are installed compared with the number of gas stations. If it is 100%, it means that there are the same numbers of

facilities as gas stations and 50% means that there is half the number of facilities.

(5) “Charging time” indicates the time required to quickly charge from the empty state to 80% of full charge in the quick charging facility on the go.

(Features common to all vehicles)

Driving performance (acceleration, power, etc.) is equivalent to gasoline cars.

The battery comes with a guarantee of 160,000 km or eight years, during which time malfunctioning batteries are repaired free of charge.

The purchaser can select the service contents of the warranty system for road-side assistance when running out of electricity at an annual fixed amount

In addition, the reduction level of greenhouse gas and air pollutant emissions during driving are the same for all vehicles.

2-4 Data collection

Data collection for BWS was conducted by means of an online questionnaire survey in January 2018. When conducting the online survey, 448 samples were selected by pre-screening. Specifically, the conditions of “driving with a certain frequency (about once in 2 weeks or more, etc.),” “car license holder,” “car owning household (not personal ownership, but possession by family members).” Only respondents who satisfied all these requirements were selected to continue answering questions in this survey.

A sample of the online questionnaire survey (448 samples) assigned an equal ratio of male and female. Regions in which respondents live are distributed nationwide, including 31 in Osaka (6.9%), 29 in Hokkaido (6.5%), 28 in Aichi (6.3%), 25 in Kanagawa (5.6%), 24 in Tokyo (5.4%) in this order. The age groups were: teens (4.5%), 20s (15.2%), 30s (18.7%), 40s (21.6%), 50s (18.5%), and 60s and older (21.4%). Regarding the car engine type, there were 381 gasoline cars (85.0%), 56 hybrid cars (12.5%), 2 plug-in hybrid cars (0.4%), and 5 electric cars (1.1%).

3 Method of object case BWS and results

3-1 Object case BWS

Table 3 shows the simple aggregate result before performing an econometric analysis with the object case BWS. The difference between the best and worst options (B–W) was aggregated. The results revealed that purchase price was valued the most, operation costs for charging was the second most valued; driving range, charging availability, and battery life and warranty were positively valued. The items that received negative values included charging time and driving performance. Reduction of CO_2 and air pollutants were the least valued. An analytical framework using a random parameter logit model will be constructed based on these results.

Table 3: Best and worst choice counts of object case BWS

Items	Best	Worst	B–W	Rank
Purchase price	1381	181	1200	1
Operation cost	804	409	395	2
Driving range	811	424	387	3
Charging availability	673	421	252	4
Charging time	556	561	−5	6
Reduction of CO_2	115	1236	−1121	9
Reduction of air pollutants	111	1147	−1036	8
Driving performance	432	584	−152	7
Battery life and warranty	493	413	80	5

3-2 Model

Based on the simple aggregate results of the BWS, as illustrated in **Table 3**, the data obtained from the object case BWS is analyzed with the random parameter logit model (Train 2003), and coefficients are estimated. The model is generally referred to as the maximum-difference (maxdiff) model (Marley & Louviere 2005). If a choice set includes a total of J items, the combination of the best and worst choices totals is $J\ (J - 1)$. In this study design, the equation for this combination can be represented as $3 \times 2 = 6$. If λ is the parameter indicating each item's importance, the probability that individuals will choose j as the best option and k as the worst option can be illustrated in Equation (1), which can be analyzed using the conditional logit model (Louviere, Flynn, & Marley, 2015).

$$P_{jk} = \frac{\exp(\lambda_j - \lambda_k)}{\sum_{l=1}^{J} \sum_{m=1}^{J} \exp(\lambda_l - \lambda_m)} \tag{1}$$

If η is a random parameter, the probability that respondents will choose j as the best option and k as the worst is L_{jk} (η), the probability density function of η is $f(\eta|\Omega)$, and Ω is the fixed parameter of this distribution; thus, the selection probability of the random parameter logit model P_{jk} is formulated as Equation (2).

$$P_{jk} = \int L_{jk}(\eta) f(\eta|\Omega) d\eta \tag{2}$$

The data obtained from the object case BWS and analyzed with the conditional or random parameter logit models is of particular importance. Further, one arbitrary variable should be excluded from the analysis in estimating the coefficient. The relative importance of the other variables is then evaluated based on the variable excluded from the analysis. In analyzing the maxdiff model, the estimated results must be interpreted considering that the signs and absolute values of the coefficient and *t*-values vary depending on the selection of the base variable.

3-3 Results of the object case BWS

The data obtained from the object case BWS was analyzed with the random parameter logit model, and **Table 4** illustrates the results. When the data in the object case BWS is estimated using the above models, one option must be excluded from the independent variables. Each of the options was excluded in turn, and the results were estimated. **Table 4** indicates only the estimated results excluding charging time, with the value of B - W closest to 0. The results from the estimation with the random parameter logit model demonstrated that all the mean parameters, excluding battery life and warranty, were statistically significant. The standard deviation parameters were also statistically significant at 1% excluding driving performance and battery life and warranty. These results showed that individual preferences varied over all variables.

Table 4: Estimation results of object case BWS by random parameter logit model

Variables	Mean parameter		S. D. parameter	
	Coefficient	t-value	Coefficient	t-value
Purchase price	2.856***	10.74	2.624***	9.25
Operation cost	0.550***	6.98	1.085***	5.78
Driving range	0.563***	6.85	1.224***	6.60
Charging availability	0.293***	4.54	0.882***	4.31
Charging time	—	—	—	—
Reduction of CO_2	−1.668***	−9.63	0.969***	4.86
Reduction of air pollutants	−1.420***	−10.50	0.662***	3.29
Driving performance	−0.321***	−5.31	0.409**	2.02
Battery life and warranty	0.047	0.89	0.406*	1.78
Number of observations	5376			
Pseudo-R^2	0.190			

Note: ***, **, * denote significance at the 1%, 5%, 10% levels, respectively.

4 Method of multi-profile case BWS and results

4-1 Model

In the multi-profile case BWS, the equation representing the combination of the best and worst options can be described as 4 × 3 = 12. The common choice experiment has a form that encourages respondents to choose one of four profile types. Meanwhile, the BWS must be formulated to choose one out of 12 combinations of the best and worst options. If β is a parameter representing each item's importance, the probability of individuals' choosing i as the best profile and i' as the worst among the choice set X is indicated as Equation (3), which can be analyzed with a conditional logit model in the case of $i \neq i'$ (Louviere, Flynn & Marley, 2015). The data was analyzed by using the random parameter logit model which enabled an assessment of preference heterogeneity.

$$P_{BW}(ii'|X) = \frac{\exp\beta'(x_i - x_{i'})}{\sum_{\substack{j,j' \in X \\ j' \neq j}} \exp\beta'(x_j - x_{j'})} \quad (3)$$

4-2 Results

Table 5 and **Table 6** are the results of the analysis of the data obtained from the multi-profile case BWS using the random parameter logit model. Different results were obtained between scenarios A and B, consistent with the predicted results. All the mean and standard deviation parameters were statistically significant in both scenarios.

Table 6 illustrates the MWTP and 90% confidence intervals, calculated with the estimated results of the random parameter logit models. A comparison using the MWTP can visualize individual evaluations. A comparison using MWTP will also be made between the scenarios. The point estimates and the confidence interval of the MWTPs were compared with the use of overlapping criteria, which indicated a statistically significant difference in the MWTPs of charging time and availability from both scenarios. A high MWTP was observed in scenario B.

Table 5: Estimation results of multi-profile case BWS by the random parameters logit model

Variable	Scenario A (cost/100 km)		Scenario B (annual savings amount)	
	Coefficient	t-value	Coefficient	t-value
Purchase price	−0.0230***	−14.82	−0.0230***	−14.62
Operation cost	−0.00649***	−10.53	0.112***	7.68
Driving range	0.00385***	12.11	0.00426***	12.57
Charging availability	0.0144***	12.14	0.0174***	13.36
Charging time	−0.0367***	−11.84	−0.0298***	−10.46
s. d. parameter				
sd_Price	0.0206***	6.92	0.0242***	8.82
sd_Cost	0.00792***	5.57	0.207***	5.78
sd_Range	0.00389***	5.71	0.00458***	7.16
sd_Availability	0.0179***	7.27	0.0185***	6.90
sd_Time	0.0513***	9.00	0.0450***	7.55
Number of observations	1792		1792	
Pseudo-R^2	0.150		0.140	

Note: *** denote significance at the 1% level.

Table 6: Marginal willingness to pay estimates

Attribute	Scenario A		Scenario B	
	MWTP	90% C I	MWTP	90% CI
Driving range (km)	1,672 JPY	[1468, 1911]	1,851 JPY	[1601, 2128]
Charging availability (%)	6,248 JPY	[5482, 7234]	7,554 JPY	[6683, 8539]
Charging time (minute)	−15,948 JPY	[−18294, −13793]	−12,924 JPY	[−15127, −10861]

Note: 90% CI (confidence interval) [lower bound, upper bound] calculated using Krinsky & Robb (1986) procedures.

5 Conclusions

In this study, object and multi-profile case BWS methods were applied to assess Japanese consumers' preferences for EVs. As a result of the relative importance of items characteristic to EVs in the object case BWS, the purchase price was given the highest importance. Although there was a big difference, the operation cost, the maximum driving distance, and the availability of the charging facility were the next. By contrast, the importance of the reduction of greenhouse gas and air pollutants, which is an important social benefit of EVs, was evaluated to be rather low. In Japan, there was little interest in social benefits from the introduction of EVs, and the result showed that emphasis was placed on the high purchase price of the vehicle. Consumers were likely to value cost attributes, whereas the alleviation of environmental damages were emphasized for incentive programs targeting consumers. This is a suggestive result for public policy encouraging the future shift to EVs and automobile company strategy.

Considering a low evaluation on reduction of greenhouse gas and air pollutants, the multi-profile case BWS analyzed 5 attributes such as purchase price. The results show that both the mean parameter and the standard deviation parameter were statistically significant for all attributes. Although respondents emphasized all the attributes applied in this study, it was confirmed that consumer preferences for those attributes were diverse.

As shown in Liao et al. (2017) and Tanaka et al. (2014), analysis of environmental attributes such as reduction of greenhouse gases is an important subject to be studied. However, with regard to Japanese consumers, it is inferred from the results of this study that consciousness concerning greenhouse gases and air pollution is still low and they are exploring possibility of purchasing EVs from a practical perspective. In addition, Lutsey and Hall (2018) point out that the effect of reducing greenhouse gas emissions through the introduction of EVs depends on the power supply configuration of each country as a result of life cycle assessment research. In countries where support and incentive programs to increase the share of EVs are implemented, it will be necessary to consider the direction of the shift to EVs, including changing power supply configuration, by continually improving the ratio of renewable energy.

The current Japanese EV market is only 0.1% of the number of domestic passenger vehicles owned, it is still at the innovation stage. The market share of next-generation models including HEVs is 11.6% and is still at the early-adopter stage. The EV shift to the early-adopter stage may be the next milestone in Japan. However, of the total volume of domestic new-car sales in 2017 (4,386,377 cars), HEVs accounted for 31.6% of the sales, while PHEVs, EVs, and CDVs accounted for 0.82%, 0.41%, and 0.02%, respectively. Further, the proportion of HEVs in the total sales of ordinary vehicles (1,548,214) and small vehicles (1,394,796) is 47.1%. Thus, the HEV market has already reached the majority even under the present circumstances. It is difficult to verify whether EVs will proliferate in the same way as HEVs. EVs should be combined with autonomous self-driving technology to stimulate different types of consumer demand, such as car sharing. To deepen knowledge about the possibility of a future shift to EVs and the direction of development, it is necessary to continue research efforts by considering experiments combining various policy options and consumer preferences.

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