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Choices of Potential Car Buyers Regarding Alternative Fuel Vehicles in South Korea: A Discrete Choice Modeling Approach

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Abstract: This study analyzes consumer preferences in South Korea for alternative fuel vehicles (AFVs), including battery electric vehicles (BEVs) and hydrogen fuel cell vehicles (HFCVs), instead of conventional fuel vehicles. A survey targeting 1500 potential car buyers in three years was conducted wherein the subjects stated their preferences depending on the varying conditions of AFV attributes and charger accessibility. Cluster-based multinomial logit and mixed logit models were developed to identify influential factors affecting consumer preferences. The models incorporated the sociodemographic characteristics of users, attitudinal perceptions, and vehicle attributes to capture their interactive impacts. The results of the estimated models suggest that a reduction in purchase price can substantially boost AFV sales, particularly those of HFCVs, with a direct elasticity of 1.78. Additionally, the models demonstrated that attitudinal perceptions, such as perceived environmental and economic benefits are significant factors. Moreover, potential car buyers who plan to buy one vehicle within one year showed the least preference for purchasing BEVs, indicating the importance of technology maturity in the BEV market. These findings can provide reasonable guidelines for establishing marketing strategies and stronger support to achieve the targeted market penetration of AFVs in a city or country.

Keywords: battery electric vehicles; hydrogen fuel cell vehicles; cluster-based multinomial logit; mixed logit model; stated preference

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1. Introduction

Over the past two decades, the issues of sustainable transportation, climate change, and air quality have garnered worldwide attention [1], with a focus on achieving the sustainability of transportation systems by minimizing greenhouse gas (GHG) emissions, air pollution, and dependence on fossil fuels. To achieve these goals, policies have been formulated to reduce gasoline consumption by lowering the driving demand and by promoting the purchase and use of alternative fuel vehicles (AFVs) [2–5]. Consequently, the automobile industry is undergoing a considerable transformation involving evolved customer needs, technological innovation, and transportation legislation to enhance green transportation systems. Rapid advancements in the development of AFVs, in particular, are expected to transform the transportation landscape in the near future [6].

AFVs are classified into numerous types, the most important of which are battery electric vehicles (BEVs) and hydrogen fuel cell vehicles (HFCVs). These two types of vehicles run on an electric motor powered by a battery or fuel cell and do not cause air pollution while operating on roads, in contrast to the internal combustion engine vehicles (ICEVs) that emit pollutants by burning fossil fuels [7]. Owing to this benefit, AFVs have garnered significant interest in recent years as an alternative to address the energy dependency and environmental concerns at both international and local levels [8]. At present, various governmental efforts are attempting to promote the purchase and wider use of AFVs; thus, it is necessary to know the factors that are important for their effective promotions. The adoption of AFVs heavily depends on certain external variables, such as stringent emissions rules, rising gasoline prices, and financial incentives [9]. Moreover, heterogeneous behavioral attitudes of users associated with their sociodemographic characteristics will determine, to some extent, their likelihood of adopting AFVs.

As part of the Paris Agreement, the government of Korea has fixed and declared a voluntary target to minimize GHG emissions by 37% by 2030 compared to the business-as-usual scenario. To achieve this voluntary target, a 34.4% reduction in GHG emissions has been planned for the transport sector by placing emphasis on electric cars, public transport, and bicycles [10]. Evidently, the Korean government has set a target that 20% of its new vehicles will be green and environmentally friendly in the near future. Moreover, new policies have been developed to promote AFV sales and emphasize the inclusion of more environmentally sustainable transport technologies in the overall mobility system of the country. However, AFVs have still not attained the desired market level despite these developments and government support. The penetration rate of AFVs accounted for only approximately 3.4% of the South Korean automobile market in 2020 [11]. To achieve a desired market level, it is essential to develop a complete understanding of the consumer preferences for AFVs.

Based on these strategic objectives, this study aims to examine the choice preferences of potential consumers who plan to buy cars in the next three years from the perspective of AFV attributes, sociodemographic characteristics of users, and their attitudinal perceptions. The study utilizes data from 1500 survey respondents to elicit customers' preferences for BEVs and HFCVs than for ICEVs. The specific AFV attributes include the purchase cost, charging time, approach time to charging stations, and driving range. As a modeling approach, this study considers both the cluster-based multinomial logit (MNL) and mixed logit (ML) models that jointly consider the heterogeneity in these attributes.

The results of this study may make several contributions. First, this study adds to the growing body of literature on identifying the factors influencing the purchase of AFVs compared with ICEVs. Previous studies have identified numerous factors, such as the sociodemographic characteristics of users, attitudes and perceptions, and vehicle-related attributes (not in conjunction). However, we argue that for a better understanding of consumer preferences, we must consider all these factors together and evaluate their interactive impacts on the adoption of AFVs. In this regard, this study aims to extend this area of research by examining the role of attitudinal perceptions, AFV attributes, and sociodemographic characteristics of the respondents. Second, the results of this study will help us to understand how changes in one set of specific attributes affect the overall decision choice of users to purchase AFVs, which is achieved by drawing vehicle attribute elasticities. This understanding will provide direct evidence of the role of user preferences on the intention of purchasing AFVs, something which can then be utilized by policymakers. Finally, the diffusion of AFVs in the existing mobility systems of cities is still in its initial phases; therefore, more studies utilizing different frameworks with new data sets produced in different time periods and geographical areas are required. This new information supports the existing literature and provides some insightful findings. These findings will have important implications for automotive industries and other stakeholders involved in designing improved strategies to motivate the purchase of AFVs. In particular, this study targets only the potential customers who are planning to buy a new car within three years, which enables more reliable results and has direct implications for growing AFV car markets.

The remainder of this paper is organized as follows. Previous studies are discussed in Section 2. The proposed models and data are described in Section 3, and Section 4 describes the statistical modeling results. Finally, a summary of the findings and conclusions of the study are provided in Section 5.

2. Literature Review

A literature review was conducted focusing on factors that affect consumers' decisions of AFV purchases. Three major factors were considered for this review: consumers' socio-demographic characteristics and attitudes, governmental policies and incentives, and AFV attributes.

2.1. Socio-Demographic Characteristics and Attitudes

AFVs have started a new era in the automobile industry. Several studies on AFVs in the United States (US), China, and European countries [12–18] have identified the key determinants of AFV adoption. For example, ref. [19] examined the determinants of AFV choice preference based on stated preference (SP) data in continental US states, excluding California, using the MNL model. The study found that the users' environmental concerns, availability of AFVs, and demographic variables have significant effects on consumer purchase expectations for AFVs. A German-based study [20] used the probit model and showed that potential car buyers in Germany currently have a low SP for electric, hydrogen, and hybrid vehicles. Their estimated results show that younger males and environmentally conscious potential car buyers have a higher preference for HFCVs and BEVs. Other studies have concentrated on the diffusion of the AFV market by investigating the impacts of consumer preferences and explaining the impacts of sociodemographic and economic variables [21–23].

Some recent studies investigated the factors that influence self-driving EV acceptance and consumer purchase intentions. For example, ref. [24] assessed whether environmental concerns influence people's intentions to purchase self-driving EVs using data from a Chinese online survey. According to the findings of the study, perceived usefulness, perceived ease of use, and environmental concern all have a positive relationship with consumers' intentions to purchase self-driving BEVs. In addition, ref. [25] examined the effects of such consumer knowledge about EVs as perceived risks, usefulness, and current financial incentives. According to the findings of the study, consumer awareness of EVs has a positive effect on perceived usefulness, attitude, and intention to purchase EVs. Ref. [26] also investigated the moderating effects of environmental traits and government support on adoption intentions in order to identify the interacting factors in the relationship between perceived value and adoption of EVs. They identified operational economic benefits and charging risk as the primary drivers or impediments to EV adoption. Furthermore, they discovered that environmental concerns and financial incentives significantly improved the perceived values of adoption intent.

2.2. Governmental Policies and Incentives

A study from China developed an extended theory of planned behavior (TPB) model by integrating psychological and policy factors to investigate whether and how policy mix characteristics affect an individual's intention to purchase EVs. It examined the direct and moderating effects of policy mix characteristics on EV purchase intention using the proposed TPB model [27]. Further, ref. [21] examined whether subsidies influenced the purchase of electric vehicles in the US and China. This study revealed that Chinese respondents have a significantly higher willingness to pay for BEV technology than US respondents. Additionally, they showed that subsidies did not change the preference order among technologies in either country.

Moreover, considerable comparative research has been conducted on government strategies and the development of AFVs across different countries. For example, ref. [28] investigated the electric vehicle (EV) incentives across Europe's five largest EV markets, including France, Germany, the Netherlands, the United Kingdom, and Norway. The study found that the incentive levels, particularly financial incentives, differed significantly among the studied nations and cities. In general, the degree of financial incentives and the density of the charging infrastructure can accurately predict the BEV market shares. Furthermore, several studies have investigated the impact of government subsidies and support policies on AFVs. To encourage the adoption of EVs, governments around the world have implemented various policy mixes, which generally include two types of policy instruments: financial and non-financial policy instruments [26].

Ref. [29] investigated the effectiveness of BEV policies at the city level and found a positive relationship between the volume of BEV sales and two demand-side policies: charging discounts and infrastructure construction subsidies. Similarly, ref. [30] attempted to investigate acceptable forms of policy tools by examining the rapid growth in BEV sales in China. Their results demonstrate that consumer-oriented policies have a significant potential to increase the adoption of BEVs.

2.3. Vehicle Attributes

Some studies have focused on BEV attributes [31–34]. Attributes such as the vehicle price, fuel cost, driving range, battery replacement cost, and charging time are among the key attributes used in consumer choice modeling [35]. To date, the main BEV attributes identified by previous studies include the purchase price [33], operation cost [36], driving range [37], charging time [38], and density of charging stations [39]. In particular, purchase and operation costs were found to negatively impact BEV adoption [40]. However, such negative effects may reduce if the consumer income rises. Notably, based on a survey of potential car buyers in Germany, ref. [13] found that consumers with high incomes are less price sensitive to BEVs. The impact of charging time also varies depending on the circumstances. For example, when the driving range is relatively short, and the density of charging stations is lower, the charging time has a more negative impact on decisions involving BEV adoption [41].

A study conducted in the U.S. [18] verified the timeframe required for traditional vehicles to replace BEVs using an optimization method. They separated BEV values into functional and non-functional attributes. Furthermore, they identified the strong effect of financial, performance, and convenience values (in the functional value category) on the adoption intention of BEVs. A study [15] that analyzed the potential demand for AFVs using the German data revealed that all AFVs were less preferable than traditional vehicles (gasoline/diesel). Moreover, the strongest preference was observed for conventional fuel vehicles despite simulations under various conditions, such as lower prices and improvements in driving range and charging times, thereby representing high consumer resistance toward eco-friendly vehicles.

This literature review clearly suggests that the choice of AFVs does not necessarily depend only on the attributes of the vehicles. This study also supports this argument by incorporating the personal perceptions of users, which may add explanatory support for consumer preferences for the adoption of AFVs. Hence, this study incorporated all three major influencing attribute themes, including AFV attributes, sociodemographic characteristics of users, and their personal attitudes. Under these model specifications, the values of direct elasticity are computed for AFV attributes, which is expected to provide policy-related insights for better AFV delivery plans. Furthermore, this study utilizes the discrete choice modeling approach, which has often been adopted for SP datasets. In particular, two similar but different models are utilized: a cluster-based MNL model accommodating the multiple-choice experiments from the same respondent and an ML model for testing the taste heterogeneity for AFV attributes. These efforts will provide a better understanding of the choice preferences of consumers adopting AFVs in the Korean context, thereby providing additional knowledge to the AFV research domain.

3. Method and Materials

3.1. Survey

An online survey dataset was obtained from Korea Institute of Civil Engineering and Building Technology, a national government-subsidized research institute. The survey was conducted by hiring a professional company in September 2019 to identify consumer preferences for BEVs, HFCVs, and ICEVs through an SP choice experiment. It collected

1500 samples comprising respondents from eight different metropolitan areas/cities of South Korea, including the capital area (that consists of cities of Seoul, Incheon, and Gyeonggi Province) and seven other major cities. A stratified sampling approach was applied to capture even distributions of age groups, gender, and residence locations. The sample proportion for each residence location was determined based on the location's population size. To obtain reliable results for the upcoming car markets, only those respondents who plan to purchase a new vehicle within the next three years were allowed to complete the survey. A structured questionnaire was developed to effectively identify three types of information from the respondents: (1) their sociodemographic characteristics; (2) personal attitudinal perceptions; and (3) stated preferences based on varying AFV attributes.

3.2. Sociodemographic Characteristics of Respondents

Table 1 presents the descriptive statistics of the variables measured in the first part of the questionnaire, the sociodemographic characteristics of respondents. The shares of male and female respondents were equally distributed in the dataset; this gender balance was planned in the sampling process to avoid sample bias by controlling participants of the survey panel. According to the age distribution, around 70% of the respondents were in their 20s and 40s, followed by those in their 50s and 60s. In terms of household size and income, around 70% of respondents had three or more people in their household, and 35.6% of respondents had a monthly household income of 4–6 million KRW (approximately 3600–5400 USD). Regarding housing tenants, 70.1% of the respondents resided in owned houses, about 71% of the participants lived in apartments, and the remainder lived in multi-family (17.8%) and single-family houses (11.4%). The majority of the respondents were self-employed (52.2%) and office workers (20.1%). The high percentage of self-employed respondents in this sample does not represent the population distribution; this may be partly attributed to the sampling strategy only targeting potential car buyers. Notably, the self-employed occupy 24.6% of the total working population in Korea [42]. Most of the survey participants (93.4%) were from Korea's capital area and major cities. This composition was planned at the survey design stage, as mentioned before.

Car owners occupied most of the respondents (about 86%). As intended, all the respondents planned to purchase a vehicle within the subsequent three years: 26.4% within one year, 49% in one to two years, and 24.6% in two to three years. Respondents reported that they mostly used vehicles for regular trips, such as traveling to work or school (52%), or for shopping purposes (22%).

3.3. Attitudinal Perceptions

The second part of the questionnaire was concerned about the attitude perceptions related to AFVs. The questions comprised six items: (1) innovativeness of the respondents, (2) their technological concerns, (3) perceived importance of subsidies on AFV use and purchase, (4) economic and (5) environmental benefits of using AFVs, and (6) the social perception when using AFVs. These were measured using a seven-point Likert scale ranging from 1 to 7 (1 = strongly disagree, 7 = strongly agree).

Table 1. Descriptive statistics of individual level attributes (n = 1500).

Category	Attribute	Description	Frequency	Proportion (%)	Population (%) [d]
Sociodemographic characteristics	Gender	Male	750	50	51
		Female	750	50	49
	Age	20–29	300	20	18.7
		30–39	370	24.6	20.3
		40–49	370	24.6	23.1
		50–59	300	20	22.7
		≥60	160	10.6	15.1
	Occupation	Self-employed	783	52.2	-
		Office worker	301	20.1	-
		Students	162	10.8	-
		Others	254	16.9	-
	Household size	1	154	10.3	37.3
		2	306	20.3	35
		≥3	1040	69.4	27.7
	Household income (million KRW/month)	Up to 4	427	28.5	-
		4–6	535	35.6	-
		6–8	283	18.8	-
		>8	255	17	
	Housing tenants	Owner	1051	70.1	-
		Lease	290	19.3	-
		Rent	159	10.6	-
	Housing type	Apartment	1062	70.8	51.1
		Multi-family	267	17.8	11.5
		Single-family	171	11.4	31.1
	Residence location	Capital area [a]	700	46.7	50.4
		Major cities [b]	700	46.7	16.1
		Other cities [c]	100	6.6	7.9
Vehicle ownership and main vehicle use	Car ownership	Yes	1289	85.9	-
		No	211	14.1	-
	Time for next vehicle purchase (years)	Within one	396	26.4	-
		1 to 2	735	49	-
		2 to 3	369	24.6	-
	Main vehicle travel purpose	Works or schools	780	52	-
		Business	168	11.2	-
		Shopping	330	22	-
		Others	**222**	**14.8**	**-**

1.0 million KRW ≈ USD 900; Note: Source for population data Korean Statistics Information System (KOSIS), http://kosis.kr (accessed on 10 March 2022); [a]: Seoul, Incheon, Gyeonggi; [b]: Busan, Daegu, Daejeon, Ulsan [c]: Chungnam, Chungbuk, Sejong; [d]: The sum of population percentages is less than 100% when the category does not cover all the classes.

To assess the innovativeness of users, respondents were asked about their willingness to adopt new technology. Technological concerns were assessed through questions about the levels of fear of new technologies, expected inconvenience while using AFVs, overall safety level, and potential difficulties such as battery depletion and system malfunctions. Regarding the importance of purchase subsidy, respondents were asked to report how much they agree or disagree with the following statements: the subsidy level will affect the degree of AFV purchase intention and use, and the tax discounts or policies providing economic benefits will help the use of AFVs. The perceptions of economic benefits were measured by asking about the potential lowering of AFV prices, along with their maintenance and operating costs, in the near future compared to conventional vehicles. The perceptions about the environmental benefits of AFVs were examined through questions about whether the spread of AFVs will help reduce air pollution and whether AFV adoption is consistent with the current environmental policies. Lastly, the social image was assessed by asking how much they agree with the following statements: AFVs are in line with social trends, and the use of AFVs will allow the people around the respondent to evaluate themselves as being ahead of most people.

The average rated scores for each item were entered as the input for the attitudinal perception variables. The computed grand means of the perception variables indicate that the respondents most strongly agreed with the importance of subsidies (5.48) and environmental benefits (5.46) of AFVs. Meanwhile, technological concerns were identified as the least important issue for adopting AFVs, as indicated by its lowest mean score of 3.94. For additional, detailed information about this part of the questionnaire, readers may refer to [43].

3.4. Choice Experiments

Descriptions of attributes and levels used in the experiment are summarized in Table 2. As mentioned earlier, three types of vehicles are considered in the choice set: BEVs, HFCVs, and ICEVs. For some respondents, the three alternatives provided may not perfectly match their specific desire, but they were forced to select one, which can be a common limitation for SP designs. These vehicle types are further described by four attributes: purchase price, charging time, driving range, and approach time to the charging station. The latter is directly associated with the charging infrastructure densities. Unlike some previous studies, operating costs (e.g., fuel and maintenance costs) were not considered in this study. This is because operating costs cannot be easily defined in a simple manner as it is heavily affected by individual travel patterns, driving habits, charging time period (e.g., daytime or late night), and other factors. For some respondents, simple operating cost assumptions may fail to appropriately reflect their travel behavior, potentially producing biased interpretations.

Table 2. Levels of vehicle attributes for the choice experiment.

Attributes	Levels		
	ICEV	**BEV**	**HFCV**
Purchase price [a] (million KRW)	23	150% | 130% | 115% | 100%	190% | 160% | 130% | 100%
Charging/refueling time (minutes)	3	50 | 40 | 20	5
Driving range (kilometer)	640	400 | 450 | 500	600 | 620 | 640
Approach time to charging/refueling stations (minutes)	5	15 | 10 | 8 | 5	30 | 25 | 20 | 15

[a] Purchase prices of BEV and HFCV can be calculated according to the reported percentages by referring to the price of ICEV; 1.0 million KRW ≈ USD 900.

To set the vehicle attributes considered, the vehicles in the Korean car market were referred to as Hyundai KONA (2020 gasoline turbo 1.6 4WD) for ICEVs; KONA EV had a 64.0-kWh battery pack for BEVs and a NEXO Fuel Cell for HFCVs. The attributes of ICEVs were fixed to single levels, reflecting the features of the referred vehicle. Four price levels were considered for BEVs and HFCVs, with the highest price levels being equal to the prices at the time of the survey, which in turn is based on the assumption that the prices of AFVs will decrease in the future owing to technological advancement and mass production. A similar assumption was applied to the charging time and driving range. In the case of charging time for HFCVs, we assumed that the current charging time would remain at the same level; thus, a single level was chosen for HFCVs. Considering the approach time to charging stations, the levels for HFCVs were assumed to be longer than those of other vehicle types, considering the lower number of installed hydrogen stations. Similarly, accessibility to charging stations for BEVs was assumed to be equal to or larger than that for ICEVs. All these assumptions reflect the current and anticipated status of the charging infrastructure supply levels in Korea.

The respondents were asked to report their most preferred vehicle among a set of three alternative vehicles based on the combinations of vehicle attribute levels. Although 6912 combinations are theoretically possible, 32 combinations obtained through a fractional factorial experimental design combining all attribute levels were utilized. A set of four combinations randomly selected from the 32 combinations were presented to a respondent, resulting in a sample size of 6000 (four choices multiplied by 1500 respondents). The overall responses revealed that around 49% of respondents were willing to use BEVs, while around 30% and 21% preferred HFCVs and ICEVs, respectively.

3.5. Models

3.5.1. Model Specification

This section describes the discrete choice modeling approach used to analyze respondents' stated choice responses for AFVs. In particular, this study utilizes the MNL model, which is a popular and extensively used discrete choice model [44,45]. The conventional MNL model can be written as follows:

$$P(y_n = j) = \frac{\exp(U_{nj})}{\sum_{i=1}^{J} \exp(U_{ni})}, \tag{1}$$

where P is the probability of choosing alternative j (Y_n = 1, 2, ..., j, ..., J), U_{nj} is the utility of individual n (n = 1, ..., N) with alternative j. Regarding the utility function, it is specifically formulated with four types of explanatory variables in the following form:

$$U_{nj} = \alpha + \beta_1 MA_{nj} + \beta_2 SED_n + \beta_3 VOU_n + \beta_4 AP_n + \varepsilon_{nj}, \tag{2}$$

where α is a constant term, β is a parameter, MA denotes mode attributes of alternative j, SED represents respondents' sociodemographic traits, VOU indexes vehicle ownership and use, AP is attitudinal perception, and ε is an error term.

To apply the MNL model, multiple observations from the same respondent should be considered to maximize the similarity within the data inside the cluster and minimize the similarity among clusters because repeated observations are bound to obtain upward-biased t-values associated with the estimated parameters [46]. To address this issue, a clustering process—the K-mean method—was simultaneously performed (we call it the cluster-based MNL model), which is similar to a panel. This approach could be used in a random-effect type of setting, wherein observations have a common latent heterogeneity [43]. In this case, the parameter estimator is unchanged, but the estimated asymptotic covariance matrix is adjusted appropriately.

The ML model was also applied to test the existence of random taste variation across individuals for AFV attributes. For this purpose, a random coefficient structure was applied by assuming that the marginal utility parameters are different by each sampled individual as follows [47]:

$$U_{nj} = \alpha + \beta_{1n} MA_{nj} + \beta_{2n} SED_n + \beta_{3n} VOU_n + \beta_{4n} AP_n + \varepsilon_{nj}, \tag{3}$$

Additionally, the independence of irrelevant alternatives (IIA) was also evaluated using nested logit forms by grouping AFVs (BEV and HFCV) in a higher nest parallel to ICEVs. However, this did not reveal statistical significance or better explanatory power than the MNL structure. The result of this evaluation is not reported in this paper for brevity.

After testing various model specifications, the variables of vehicle attributes were defined as generic while all others were entered as alternative-specific variables. In the final models, only significant variables (significance level ≤ 0.1 or less) were retained for brevity. In this case, all the individual variables in a sub-category (e.g., age and occupation) were retained for comparisons when at least one variable in the sub-category was significant. For example, for the age variable, when one age-bin (e.g., 20s) is significant, all other age bins are also retained in the model.

3.5.2. Direct Elasticity

The estimated coefficients of attributes indicate a marginal change in utility, which is the change in utility caused by changing the attribute by one unit. As the units of each attribute are different, the magnitudes of the estimated coefficients cannot be compared directly. Consequently, we calculated the direct elasticity to compare the impact of the attributes. The direct elasticity, $E_{x_{ik}}^{P(i)}$ for alternative i and attribute k, represents the uniform percentage change in the choice probability due to the percent change in x_{ik} across all members of the group. The following equation was used for the direct elasticity [48]:

$$E_{x_{ik}}^{P(i)} = \frac{\partial P(i)}{\partial x_{ik}} . \frac{x_{ik}}{P(i)} = \frac{\partial lnP(i)}{\partial ln x_{ik}}, \tag{4}$$

$$E_{x_{ik}}^{P(i)} = [1 - P(i)] x_{ik} \beta_k, \tag{5}$$

where $P(i)$ is the expected share of the group choosing alternative i, and β_k is the estimated parameter for variable k from the model.

4. Results and Discussions

4.1. Models

The results of the cluster-based MNL and ML models are presented in Table 3. The two modeling approaches did not produce different outcomes in terms of estimated parameters and the goodness of fit measures. However, the ML model has a slightly higher McFadden pseudo R^2 value. Moreover, the two models consistently prove that all experimentally varied vehicle attributes, except the approach time to charging stations, significantly impact the choice decision with expected signs. In particular, the vehicle cost and charging time have a negative impact on preference. In contrast, a longer driving range has a positive impact. This finding is largely consistent with previous studies that highlighted that the factors of cost, charging time, and driving range were the main challenges to be overcome by AFVs [41,49]. The insignificance of the approach time to charging stations is unexpected, although the sign is intuitively negative. To explain this situation, further examination is required by applying different experimental designs.

Table 3. Estimation results in the discrete choice models.

Category	Variables/Reference Variable	Variable Description	Cluster-Based MNL Model			Mixed Logit Model		
			ICEV	BEV	HFCV	ICEV	BEV	HFCV
Attributes		Vehicle cost (100,000 KRW)		−0.006 *			−0.007 *	
		Charging/refueling time (minutes)		−0.004 **			−0.005 **	
		Approach time to charging/refueling stations (minutes)		−0.001			−0.002	
		Driving range (km)		0.002 ***			0.003 ***	
Sociodemographic characteristics	Age (Ref. = 60s)	20s	−0.056	-	−0.057	-	-	−0.057
		30s	−0.202 *	-	−0.229 *	-	-	−0.204 *
		40s	−0.065	-	−0.070	-	-	−0.071
		50s	−0.101	-	−0.104	-	-	−0.105
	Occupation (Ref. = others)	Self-employed	0.391 **	-	0.396 *	0.393 **	-	0.399 **
		Office worker	0.244 *	-	0.248 *	0.244 *	-	0.253 *
		Student	−0.019	-	−0.024	0.023	-	−0.060
	Household size (Ref. = one)	Two	-	−0.098	-	-	−0.128	-
		Three or more	-	−0.220 *	-	-	−0.232 **	-
	Housing tenant (Ref. = monthly rent)	Owner	0.217 *	0.206 **	-	0.219 *	0.199 **	-
		Lease	0.209	0.162	-	0.214	0.129	-
	Household income in million KRW (Ref. = 6–8)	Up to 4	−0.054	−0.116	−0.055	−0.091	-	−0.101
		4–6	−0.189 *	−0.145 *	−0.188 *	−0.156 *	-	−0.202 *
		≥8	−0.013	−0.119	−0.015	−0.017	-	−0.109
Vehicle ownership and use	Car ownership	Own	0.257 *	0.248 **	-	0.213 **	0.192 **	-
	Vehicle purchase plan (Ref. = 2–3 years)	Within 1 year	-	−0.126 *	-	-	−0.129 *	-
		1 to 2 years	-	−0.075	-	-	−0.078	-

Table 3. *Cont.*

Category	Variables/Reference Variable	Variable Description	Cluster-Based MNL Model			Mixed Logit Model		
			ICEV	BEV	HFCV	ICEV	BEV	HFCV
	Travel purpose (Ref. = others)	Work or school	0.226 *	-	0.532 *	0.268 *	-	0.441 *
		Business	0.080	-	0.398 *	0.154	-	0.308 *
		Shopping	0.058 *	-	0.359 *	0.106	-	0.260
Attitudinal perception		Innovativeness	-	0.005	−0.081	-	0.004	−0.080
		Technological concern	-	−0.018	−0.027	-	−0.019	−0.029
		Purchase subsidy	-	−0.009	−0.023	-	−0.010	−0.025
		Economic benefits	-	0.023	0.073 *	-	0.024	0.069 *
		Environmental benefits	-	0.052 *	0.039	-	0.053 *	0.038
		Social image	-	0.015	−0.022	-	0.016	−0.020
	Constant		−0.789 *	0.238 *	-	−0.806 *	0.329 *	-
Standard Deviation		Driving range (km)	-	-	-		0.001 *	
Summary								
		Number of cases (respondents)	6000 (1500)			6000 (1500)		
		Log-likelihood (0)	−6591.7			−6591.7		
		Log-likelihood (ß)	−6183.6			−6183.1		
		McFadden Pseudo R^2	0.061			0.062		

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; Note: ICEV = internal combustion engine vehicle; BEV = battery electric vehicle; HFCV = hydrogen fuel cell vehicle.

Some sociodemographic variables were excluded from the final models because of their insignificance. The excluded variables were gender, housing type, and location of residence. Notably, the influential variables can be varied depending on the survey design methods, study location, and study year, as suggested by the literature review conducted by [38]. The estimated alternative-specific constants (e.g., 0.238 and −0.789 for BEVs and ICEVs, respectively, in the cluster-based MNL model) indicate that respondents mostly preferred BEVs, followed by HFCVs and ICEVs. This is consistent with the revealed portions of the vehicle type choices, as presented above (refer to "Choice experiments" in Section 3.4).

The final ML model revealed that the impact of driving range can be heterogeneous across respondents, as suggested by the significance of the estimated standard deviation of the driving range parameter. As the estimated parameter β_k follows a normal distribution, for $N(b_k,\ w_k)$ with a mean of b_k and variance of w_k, the ML model indicates that approximately 1.5% of the population may have a negative driving range parameter. We speculate that some respondents might pay little attention to the driving range and assign more value to other attributes. Some might have short daily driving distances that can be sufficiently covered by the shorter driving ranges of some AFVs.

4.2. Factors Associated with AFV Preferences

Regarding the sociodemographic variables, the results of the model show that respondents in their 30s are less likely to purchase ICEVs and HFCVs. In particular, we observed a stronger resistance to HFCVs; in the ML model, the parameter representing the age group of 30 years old was the only significantly negative parameter. This may imply that potential car buyers in that age group may prefer BEVs to other vehicle types. Notably, some previous studies have shown a rather insignificant impact of age variables on BEV purchase intention [49,50]. The estimated coefficients of self-employed and office workers indicate significant and positive impacts on the preferences of ICEVs and HFCVs. This may explain why the respondents in that occupation category were concerned about the short driving range of BEVs, which is inadequate to meet their travel needs. Regarding the household size, large households with three or more family members showed a significantly negative impact on BEV preferences. This indicates that respondents with a large family prefer full-sized cars. This can also be understood by the fact that current BEVs in the market are mostly small. The significantly positive coefficient of the owner in the category of housing tenants suggests that people who own a house are more interested in choosing BEVs than HFCVs. This may be reasonable because house owners will likely have parking facilities or spaces that can be equipped with BEV chargers. However, homeowners still exhibit a higher preference for ICEVs. Regarding the household income, respondents in the income group of 4–6 million KRW tend to have a lower preference for HFCVs and a relatively higher preference for BEVs. This is clearly illustrated in the ML model. In particular, the respondents in the middle-income group are more likely to purchase BEVs that are environmentally friendly but relatively cheaper than HFCVs.

Ref. [51] found that car ownership had no significant effect on BEV adoption. However, the estimated models in this study show that current car owners have a strong tendency to buy ICEVs or BEVs and are less likely to purchase HFCVs. Notably, respondents seem unlikely to purchase BEVs within one year, as suggested by the significantly negative estimated coefficient of the within the one-year variable. This is because people in this group may wait for better BEV technology. Considering the variables related to traveling, we found that HFCVs are generally preferred for mandatory or regular travel purposes such as work/school and business. This may be due to the expected reliability and long driving range of HFCVs, despite their high purchase costs.

Considering the attitudinal perception variables, the models estimated two significantly positive variables: economic benefits for HFCVs and environmental benefits for BEVs. This finding indicates that respondents who have positive perceptions of the benefits of AFVs are more likely to purchase AFVs. Notably, the more the perceived economic benefits of AFVs, the more is the preference for HFCVs. This may be related to the relatively higher price of HFCVs. The results also predict that there will be a higher demand for BEVs among those who consider the environmental impacts of cars. Despite these findings, it is rather counterintuitive that other attitudinal perception variables are not significant. Previous studies have often argued that consumers' perceptions are an important factor in AFV preference. Additionally, the magnitudes of the significant attitudinal parameters (e.g., 0.069 and 0.053 in the ML model) appear to be marginal compared to other significant parameters in other personal characteristics categories. This implies that their impacts are relatively minor, as indicated by [41].

4.3. Direct Elasticity

Direct elasticities were estimated for each attribute of BEVs and HFCVs based on the parameters from the ML model, mid-level values in the SP experiment (refer to Table 2), and the choice shares of the sample. Consequently, the price elasticity was found to be noticeably greater for the attributes of vehicle price and driving range, as shown in Figure 1. In particular, the choice of HFCVs is very sensitive to price. For example, a 10% reduction in price can boost HFCV's market share by approximately 18%. For HFCVs, the driving range elasticity (1.302) is also elastic as the value is greater than 1.0. These findings indicate that the preference for HFCVs is heavily influenced by vehicle attributes. This is plausible because people were unlikely to be familiar with HFCVs, and thus, might mostly rely on vehicle price and performance. Meanwhile, the charging time elasticity was found to be marginal, which may be partly attributed to the SP experiment design, wherein only a single level of charging time was partly attributed to the SP experiment design, for which in turn only a single level of charging time was considered for ICEVs and HFCVs. Consequently, this elasticity analysis suggests that AFV preference is sensitive to the purchase price, and thus, its reduction is the most effective way to increase consumers' preferences.

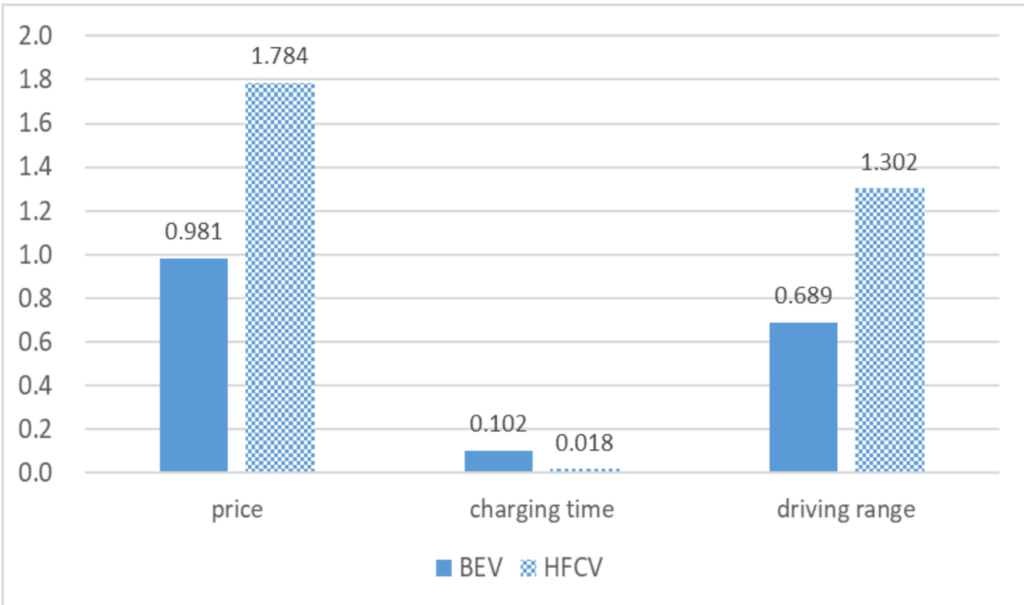

Figure 1. Estimated direct elasticity (absolute value). Note: Actual values are negative for the price and charging time.

5. Conclusions

The promotion of AFVs has emerged as a significant effort in reducing global CO_2 emissions from the transportation sector. This study examined consumer preferences for AFVs, targeting potential consumers who planned to buy cars in the next three years from the following perspective: sociodemographic characteristics of users, attitudinal perceptions, and AFV attributes. We applied two discrete choice models, the cluster-based

MNL and ML models, and estimated the direct elasticities of vehicle attributes to measure the sensitivity of the impacts of attributes. The statistical models produced interpretable results, revealing the factors that influenced choice decisions. The following major findings obtained from this study can potentially increase sales in the AFV market and promote their widespread application in transportation systems.

First, the impacts of financial and technical attributes of AFVs on the market share were found to be significant, such as the purchase price, driving range, and charging time. Our findings suggest that consumers are more likely to adopt an AFV if they recognize it is financially affordable and technically acceptable, which was clearly proven by the estimated elasticities. Notably, the demands for HFCVs were elastic due to changes in price (1.784) and driving range (1.302). Thus, dropping the AFV price and increasing the driving range are effective ways to increase consumers' preferences. The ML model reveals that the impact of the driving range could be heterogeneous across respondents. This illustrates that consumers' responses can vary depending on their travel behavior and attribute valuations. It is plausible that accepting a certain level of driving range can be directly connected to the travel behavior of customers (e.g., the daily travel distance).

Second, considering the sociodemographic characteristics, the models revealed that respondents in their 30s were more inclined to adopt BEVs. Meanwhile, members of larger households and those who use their current vehicles for work or school are reluctant to purchase BEVs. These findings indicate that customized AFV marketing strategies are required to boost the share of AFVs. Notably, potential car buyers who plan to buy one within one year showed the least preference for purchasing BEVs, indicating the importance of technology maturity in the BEV market. This can be interpreted as the willingness of people to buy a BEV but postponing its purchase for at least one year. Marketing strategies should be developed based on the existing prowess of BEV technology.

Third, attitudinal perceptions, such as perceived economic and environmental benefits, were also significant. In particular, the perceived economic benefit is more related to HFCVs, and the adoption of BEVs is closely linked to the perceived environmental benefits. This indicates that a particular type of AFV can be connected to specific perceptions. Although this study did not attempt to identify the reasons for such connections, such investigations would help develop effective marketing strategies depending on the AFV type. Surprisingly, except for the two perceptions mentioned above, others were not identified as significant.

This study is expected to provide valuable information to policymakers and auto manufacturers in developing various policies and strategies. The findings may also be useful to other countries with relatively low AFV market penetration rates, who are attempting to enhance and evaluate their sustainable mobility systems. From the theoretical perspectives, this study also contributes to the body of knowledge regarding behavioral responses of consumers in car market. As already indicated, this study confirmed that vehicle purchase decisions are made in a complicated manner, combining vehicle attributes and consumers' socio-demographic and attitudinal characteristics together. In addition, consumers' car ownership and car use patterns were identified to be influential to some degree. This suggests both research opportunities and challenges concerning how to effectively combine various factors and how to discern the magnitudes of their impacts.

This study can be further improved by addressing some limitations. The relatively low explanatory power of the estimated models is an area that should be improved. According to the study design, many other potentially influential variables were not included in our models, such as vehicle operation and maintenance costs and detailed driving habits of individuals. The hypothetical SP choice experiment method is the main limitation of this research, as it applies only a narrow range of varying conditions. It also should be noted that some potential biases can be introduced by asking the attitudinal questions before the choice experiments. Since the attitudinal questions include some that are AFV-related (e.g., environmental concerns and purchase subsidy), the respondents might reply in favor of AFVs. In future research, a better survey design that can capture more important variables and minimize potential biases should be developed.

Future researchers can apply different methods of data analysis, such as machine learning and multi-criteria decision-making approaches, to investigate consumer preferences for AFVs. Hybrid choice models (HCMs) would be an alternative approach when incorporating attitudinal variables [52,53]. This is because including the attitudinal indicators directly in the utility function, which is the approach in this study, can lead to inconsistent estimates. The attitudinal indicators likely contain measurement errors. Moreover, due to the correlation between the indicators and the error of the utility, endogeneity bias can easily occur. Regarding employed data, as an increasing number of AFVs are operated on roads, future studies may be able to apply preferences that can more realistically reflect the behavioral responses of consumers under a wider range of conditions.

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