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Feasibility Study on the Korean Government's Hybrid Conversion Project of Small Diesel Trucks for Parcel Delivery Services

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Abstract

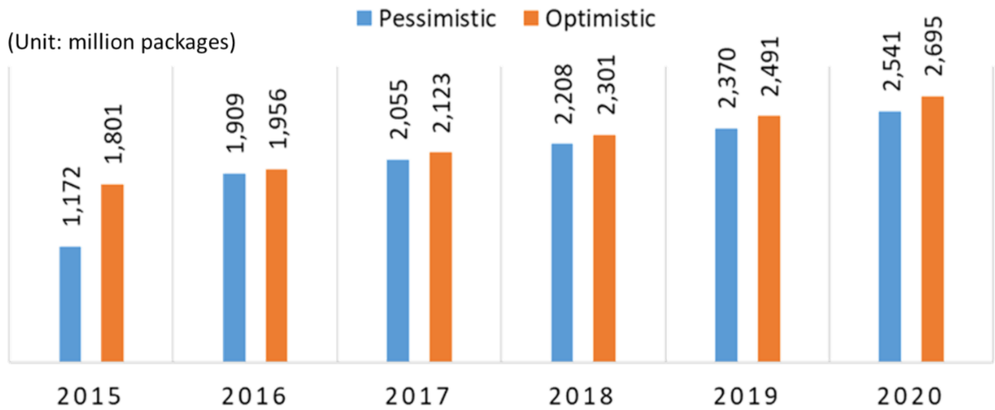
The Korean government is planning an R&D project to convert existing small diesel trucks for parcel delivery services to hybrid vehicles as part of its effort to reduce emissions of greenhouse gases and particulate matter (PM). This project started from the realization that parcel delivery trucks have become one of the main sources of PM emissions as the parcel delivery service industry has rapidly grown in Korea amid inefficient driving environment for delivery trucks. To evaluate the marketability and feasibility of the project, this study analyzed truck owners' preferences for converting to hybrid vehicles. Hierarchical Bayesian choice-based conjoint analysis was employed to forecast conversion probabilities and willingness to pay based on different vehicle attributes, and the influencing demographic factors were then analyzed. The findings are expected to enable decision makers to set a reasonable budget for hybrid conversion based on demand forecasting results. For policy implications, the results suggest that truck owners should be allowed to pay for the conversion in installments, not in a lump sum, and it would be strategically effective to target the consumer segment that prioritizes saving fuel costs relative to other attributes to promote hybrid conversion.

Keywords: hybrid conversion, small diesel trucks, demand forecasting, Hierarchical Bayesian, Korean government

1. Introduction

Changing consumer behavior and the rising popularity of e-commerce have spurred the growth of the parcel delivery service market in Korea. The number of packages delivered was about 1.3 billion units in 2011 which increased to more than 2.3 billion units in 2017, with a spectacular annual growth rate between 7.3% and 13.3% (Maritime Press of Korea, 2018). The average number of uses of parcel delivery services, by persons aged 13 years and older, soared from 3.0 times a year in 2000 to 35.7 times a year in 2013. As of 2013, the number of parcel delivery trucks of less than 1.5 tons was a total of 36,734 units, including 24,721 commercial vehicles and 12,031 privately owned vehicles. In 2014, sales increased by 6.4% from the previous year at KRW 3.97 trillion (Ministry of Land, Infrastructure and Transport of Korea, 2016). It is projected that the parcel delivery market will continue to grow as an increasing number of shoppers make online and direct overseas purchases. Figure 1 shows the prospects of domestic parcel delivery volume provided by the Ministry of Land, Infrastructure and Transport of Korea (MOLIT).

Figure 1. Prospects of Domestic Parcel Delivery Volume (MOLIT, 2016)



Note: Pessimistic and optimistic estimates are produced by applying 3.0% and 3.5% of GDP growth rate, respectively, in the formula of forecasting demand.

Last mile deliveries are usually made by small 1-ton trucks in Korea, most of which are diesel vehicles that emit particulate matter (PM) and greenhouse gases, which have serious social and environmental implications. To make matters worse, parcel delivery trucks generally drive in the city and thus frequently accelerate and decelerate. Consequently, their average fuel economy is only about 3 km/l, which is much lower than a commonly used combined fuel economy of about 9 km/l. Hence, parcel delivery trucks are considered to be a relatively more significant source of PM and greenhouse gas emissions. In fact, 52% of ultrafine particles in Seoul is from transportation (vehicles, construction vehicles, and others) of which diesel vehicles are responsible for 67% of emissions of oxides of nitrogen (NOx), the primary source of ultrafine particles. By usage, freight cars and construction vehicles account for the highest proportion at 54%. Moreover, PM emissions of diesel vehicles amount to about 12,969 tons, accounting for about 62% of total vehicle emissions in the country. Diesel trucks, specifically, are responsible for about 68% of the total PM emissions produced by diesel vehicles (MOLIT, 2016).

In addition to greenhouse gases and PM emissions, rising logistics costs due to increases in international oil prices calls for development of core technologies that maximize fuel economy with low costs. However, such technologies cannot be developed without government involvement due to the high development costs. Globally, the introduction of hybrid and electric vehicles is a critical issue for policymakers. Countries with large domestic auto markets, such as the United States or China, have aimed to promote green cars through subsidies, and studies on feasibility and effectiveness of relevant policies are ongoing (Zhang et al., 2018, Kang et al., 2016).

The Korean government is also trying to reduce PM and greenhouse gas emissions from parcel delivery trucks by developing a range of technologies as part of a national R&D project, and hybrid parcel delivery trucks have been selected as one of its short-term alternatives (MOLIT, 2016). The project targets small diesel trucks that have already been sold or that are yet to be sold in the market. The technology involves converting existing diesel trucks to diesel-electric hybrids, which are expected to produce lower PM and greenhouse gas emissions. Compared to purely electric trucks, the emissions of PM and greenhouse gases of diesel trucks will be relatively higher. However, the technology of converting to hybrid trucks will involve a low installation cost per unit with an insignificant addition to vehicle weight, and it will be readily applicable to the vehicles already in the market thus can be implemented in a short period of time. To maximize these advantages, the project set the following technological aims: conversion cost of KRW 5 million or less, weight addition of 100 kg or less, fuel economy improvement of 30% or higher, and PM/greenhouse gas emissions reduction of 20% or more.

Table 1. Project Agenda of Converting Parcel Delivery Trucks to Hybrids by the Korean government (MOLIT, 2016)

Division	Sub-division
Policy, law, and institutional reforms to commercialize technologies	Institutional supplementation for the conversion project
	Legal and institutional support
	Study on marketability and economic feasibility (the objective of this study)
Conversion technology for diesel-electric hybrid trucks	Logistics environment analysis technology
	Diesel-electric hybrid power-train design technology
	Diesel-electric hybrid truck conversion technology
Control technology for diesel-electric hybrid trucks	Diesel-electric hybrid power-train control technology
	Electric system management technology
	Controller implementation technology

The project agenda can be divided into three categories, as shown in Table 1: (a) policy, law, and institutional reforms to commercialize technologies, (b) conversion technology for diesel-electric hybrid trucks, and (c) control technology for diesel-electric hybrid trucks. This study focuses on assessing marketability and economic feasibility as part of the efforts to reform policies/laws/institutions for technology commercialization. To do so, the costs of technology dissemination in the market need to be estimated with information on expected production costs, revenue-expense structure of the parcel delivery truck owners, and drivers' willingness to pay for the technology. The size of the market demand for the technologies can then be determined. In addition, the economic feasibility of the conversion technology needs to be assessed by evaluating expected benefits and costs of developing and distributing technologies.

Within this context, this study identifies the demographic factors influencing parcel delivery truck owners' willingness to convert diesel trucks to hybrids and forecasts demand for such conversion when the technology becomes available in the market. Choice-based conjoint analysis is used, and heterogeneous preferences of individual consumers are modeled using Hierarchical Bayesian (HB) estimation (Green and Krieger, 1996, Lenk et al., 1996, Rossi and Allenby, 2003, Rossi et al., 2005).

Conjoint analysis is one of the most widely used statistical methods in a variety of disciplines, including marketing, economics, and engineering to model consumer preferences for a product or service. It is also frequently used to study consumer preferences and estimate willingness-to-pay regarding green products (Kaufmann et al., 2013, Lieder et al., 2018, Meyerding and Merz, 2018) and sustainable energy infrastructure (Álvarez-Farizo and Hanley 2002, Zaunbrecher et al., 2017). For instance, Olson (2013) showed that consumer preferences for green products may dramatically decrease when its attributes conflict with conventional attributes. According to the author, this is because higher price, smaller size, and lower performance often associated with green products tend to negatively influence consumer preferences. In addition, conjoint analysis is used in studies on environmentally friendly policy making decisions beyond simply evaluating green products (Lüthi and Prässler, 2011, Gao et al., 2016, Shin and Hwang, 2017, Peterson and Feldman, 2018).

Conjoint analysis is also extensively used in studies on consumer preferences regarding alternative fuel vehicles, such as one in this study (Olson, 2018, Struben and Sterman, 2008, Diamond, 2009, Golob et al., 1997, Ewing and Sarigollu, 1998, Goldberg, 1998, Brownstone et al., 2000, Mannering et al., 2002, Bunch et al., 1993, Dagsvik et al., 2002, Bolduc et al., 2008, Axsen and Kurani, 2010, Lee and Cho, 2009, Heywood et al., 2004, Lee et al., 2013, Kang et al., 2015, Kang et al., 2016, Kang et al., 2017a, Kang et al., 2018, Lee et al., 2017). Consumer preferences regarding alternative vehicles may vary depending on the region or country. Therefore, it is necessary to compare consumer preferences in different markets in order to make a decision suited for a given market (Helveston et al., 2015; Kang et al., 2016). Furthermore, a consumer preference model on alternative vehicles established with conjoint analysis can also be applied to the engineering design of optimized green cars (Kang et al., 2015, Kang et al., 2016, Kang et al., 2017a, Kang et al., 2018, Lee et al., 2017).

Much previous research has centered on examining consumer preferences regarding *new* purchase decisions for electric and hybrid vehicles. Moreover, although there are studies focusing on the optimal timing of replacing current vehicles with hybrid ones (He et al., 2017), little attention has been devoted to consumer preferences with respect to hybrid conversion of the cars that they already drive. In analyzing consumer preferences regarding hybrid conversion of parcel delivery trucks, this study has the following aims: (1) modeling hybrid conversion preferences and calculating the importance of attributes (Section 3.1), (2) predicting the probability of choosing conversion (Section 3.2), (3) calculating consumers' willingness to pay (Section 3.3), (4) classifying consumers according to the importance of certain attributes (Section 3.4), and (5) analyzing demographic factors that influence the importance of attributes (Section 3.5).

This study is organized as follows: Section 2 introduces the concept of HB choice-based conjoint analysis; Section 3 presents the analysis results; Section 4 analyzes the results and provides related insights; and Section 5 draws conclusions and notes the limitations of the study.

2. Methodology

2.1 Hierarchical Bayesian Choice-based Conjoint Analysis

HB choice-based conjoint analysis is the most widely used method to predict consumers' heterogeneous demands for new products in economics and marketing research (Lenk et al., 1996, Rossi and Allenby, 2003, Rossi et al., 2005). Consumers' choice data are collected through surveys, and HB estimation is used to establish a model of individual consumer's utility. Recently, the model accuracy has been improved with the application of a variety of machine learning methods (Toubia et al., 2007, Kang, 2014).

A random utility model to quantify consumer preference is represented as follows (Green and Krieger, 1996).

$$u_{ij} = v_{ij} + \varepsilon_{ij} \tag{1}$$

u_{ij} denotes utility, v_{ij}, a deterministic component of utility, ε_{ij}, an error component that cannot be observed for, i, an individual, and j, an alternative from which to choose from. It is assumed that consumers choose a product that maximizes their utility among the available options. v_{ij}, the definitive component as a utility of observables, can be represented as a linear function of attributes, such as product price and performance, as follows.

$$v_{ij} = \sum_{k=1}^{K} \sum_{l=1}^{L_k} \beta_{ikl} z_{jkl} \tag{2}$$

z_{jkl} is a binary variable that is equal to 1 for alternative j with level l of attribute k. A level refers to a value from a range of variation an attribute can take. β_{ikl} refers to a partworth of level l of attribute k for individual i. This represents the partial utility that a consumer assigns for a certain attribute level. Partworth β_{ikl} can be estimated through consumer survey data and HB estimation. Consumer survey data are gathered using a choice-based survey, which is conducted by presenting three product alternatives to consumers and asking them to choose the most preferred product of a bundle of attributes. These alternatives specify three possible combinations of different levels of attributes of a product. The choice of “none” is also given when none of the options is preferred.

HB estimation to measure partworth by consumer, β_{ikl}, consists of two levels. In the higher level, it is assumed that β_i, the utility of an individual, follows a multivariate normal distribution, $N(\boldsymbol{\theta}, \boldsymbol{\Lambda})$. $\boldsymbol{\theta}$ denotes the mean vector of the individual distribution, while $\boldsymbol{\Lambda}$ denotes the covariance matrix of the distribution. In the lower level, probability is used with a logit model, which is represented by the following equation.

$$P_{ij} = \frac{e^{v_{ij}}}{\sum_{j' \in J} e^{v_{ij'}}} \tag{3}$$

P_{ij} in the equation represents the probability of individual i choosing alternative j within the set of alternatives j. Markov Chain Monte Carlo (MCMC) is used to estimate the utility of an individual. This study discarded the initial 50,000 iterations of the total 100,000 iteration results, and only the first of ten iteration draws were used. This is a frequently used method to lower autocorrelation in the chain. With information on probability P_{ij}, it is possible to predict the market share of a new product. In addition, an importance of an attribute can be computed, which is a measure that indicates how much an attribute contributes to one’s utility relative to other attributes. More precisely, with the utility function modeled, an attribute importance is calculated as a range of partworths of a given attribute (i.e., difference between maximum and minimum partworths of a given attribute) divided by the total sum of partworth of each attribute.

2.2 Conjoint Survey Design

There are largely three ways in which a researcher can elicit consumer preferences in surveys: ranking, rating, or choice. Nowadays, choice surveys are known to be the best predictor of consumer behavior since it closely resembles their actual behavior. To evaluate small parcel delivery truck owners’ and drivers’ willingness and preferences for conversion to hybrid vehicles, the respondents were presented with hypothetical profiles with multiple choices and asked to indicate their most preferred alternative. Each choice represents a bundle of levels of attributes. In order to obtain respondents’ preference data, attributes that are deemed essential when making decisions before converting to hybrids were included, and those related to the conditions after conversion were also considered. Transportation experts in government and universities were interviewed, and key attributes related to conversion decision narrowed down to the following three: fuel cost savings, hybrid conversion costs, and battery replacement costs. The definitions and levels of each attribute are as follows and are summarized in Table 2.

- Fuel cost saving effect (%): This is the degree of fuel cost savings after converting a truck to a hybrid. This consists of four levels of savings, including a 15%, 20%, 25%, and 30% reduction in fuel costs from that of the previous diesel truck.
- Hybrid conversion cost: This is incurred when converting a truck to a hybrid vehicle such as manufacturing costs, installation costs, etc. Four levels of cost are suggested: 100, 250, 450, and 600 (unit: KRW 10,000).
- Battery replacement cost (four-year cycle): This is generated by replacing battery every four years after conversion. Four levels of cost are considered: 35, 45, 55, and 65 (unit: KRW 10,000/ 4 years)

Table 2. Attributes and Levels of Hybrid Truck Conversion

Attribute (unit)	Description	Attribute level (Level 1~4)
Fuel cost saving (%)	Fuel cost saved after hybrid conversion	15 / 20 / 25 / 30
Hybrid conversion cost (unit: KRW 10,000)	Cost required for hybrid conversion	100 / 250 / 450 / 600
Battery replacement cost (unit: KRW 10,000/4 years)	Cost generated every four years after conversion for replacing the battery	35 / 45 / 55 / 65

Note: KRW 10,000 was equal to approximately USD 8.85 as of 2017
(Source: https://data.oecd.org/conversion/exchange-rates.htm).

After determining the attributes and levels related to hybrid truck conversion technology, profiles with a combin ation of attributes and levels are generated using the D-optimal design methodology to create questionnaires for a conjoint survey. Figure 2 shows an example question from the survey of the study.

Figure 2. Example of the Conjoint Survey

Q: Please choose one that you prefer the most from the following options.
If there is none, choose "no conversion."

(unit: KRW 10,000)

Attributes	Option A	Option B	Option C	No Conversion
Fuel cost savings	20%	30%	30%	(keep the current diesel truck)
Hybrid conversion cost	250	600	100	
Battery replacement cost (4-year cycle)	35	35	45	
Choose (V)	☐	☐	☐	☐

The conjoint survey was designed by associating general preference trends (e.g., higher fuel cost savings are better) with respect to three elements of fuel cost savings, hybrid conversion costs, and maintenance costs. Respondents were asked to consider a variety of levels of attributes with respect to the hybrid truck conversion profiles and to choose the most preferred from the three options. A 4th option, "No conversion," could also be selected. The 10th question, of a total of 16 conjoint survey questions, was used to determine whether respondents answered the questions sincerely (i.e., sanity check). This question had one conversion option superior in all attributes compared to the other choices, and evidently, there was only one rational answer.

2.3 Subjects of the Survey

The survey was completed for 245 owners of small parcel delivery trucks (1.5 tons or less) sampled equally from the five major cities in Korea, including Seoul, Busan, Daejeon, Daegu, and Gwangju. All the respondents selected were owners of their vehicles, while drivers of business-owned trucks were excluded from the survey. After they were filtered using a sanity check question, 191 valid subjects were obtained for the sample. The survey was commissioned by Metrix, a research and polling organization in Korea, in 2017 and conducted through face-to-face interviews in Korea's five major cities (Metrix, 2017).

In addition to the conjoint survey questions, the respondents were presented with questions regarding their demographic and vehicle information, such as annual income, average monthly fuel cost, average daily mileage, and fuel economy of one's vehicle. In total, 191 respondents have worked in parcel delivery services for 7 years and 8 months on average. The highest portion of respondents make KRW 30.01 to 35 million a year (29%), followed by those earning KRW 25.01 to 30 million (27.3%) and those earning KRW 35.01 to 40 million (14.3%). According to the survey, the average monthly fuel cost is KRW 348,000, and the average daily mileage is 49.6 km. The fuel economy of the parcel delivery trucks of the respondents is 7.0 km/l on average. This is probably because parcel delivery trucks mostly operate around cities which contributes to their lower fuel economy. Also, 91.6% of the respondents are self-employed, and 8.4% own trucks as a representative of a company. In all, the survey results showed that 28.8% of 191 respondents had a positive view towards converting their vehicles to hybrid ones, citing reasons such as fuel cost savings and emissions reduction.

3. Results

3.1 Consumer Preference Modeling and Attribute Importance

The individual utility function results, i.e. average partworths by attribute level, of the hybrid conversion of parcel delivery trucks are summarized in Table 3. Again, these are calculated from HB estimation using survey data.

Table 3. Partworth Analysis of Attribute Levels and Importance

Attributes	Importance	Level		Partworth
Fuel cost savings	21.0% (31.0)	Level 1	15%	-1.67 (2.02)
		Level 2	20%	-0.08 (0.29)
		Level 3	25%	0.38 (0.47)
		Level 4	30%	1.21 (1.64)
Hybrid conversion cost (unit: KRW 10,000)	69.1% (29.7)	Level 1	100	7.03 (4.18)
		Level 2	250	3.95 (2.61)
		Level 3	450	0.92 (2.03)
		Level 4	600	-11.90 (8.21)
Battery replacement cost (unit: KRW 10,000)	9.9% (7.5)	Level 1	35	1.08 (0.89)
		Level 2	45	0.45 (0.37)
		Level 3	55	0.04 (0.26)
		Level 4	65	-1.57 (1.25)
No conversion		-		7.17 (9.52)

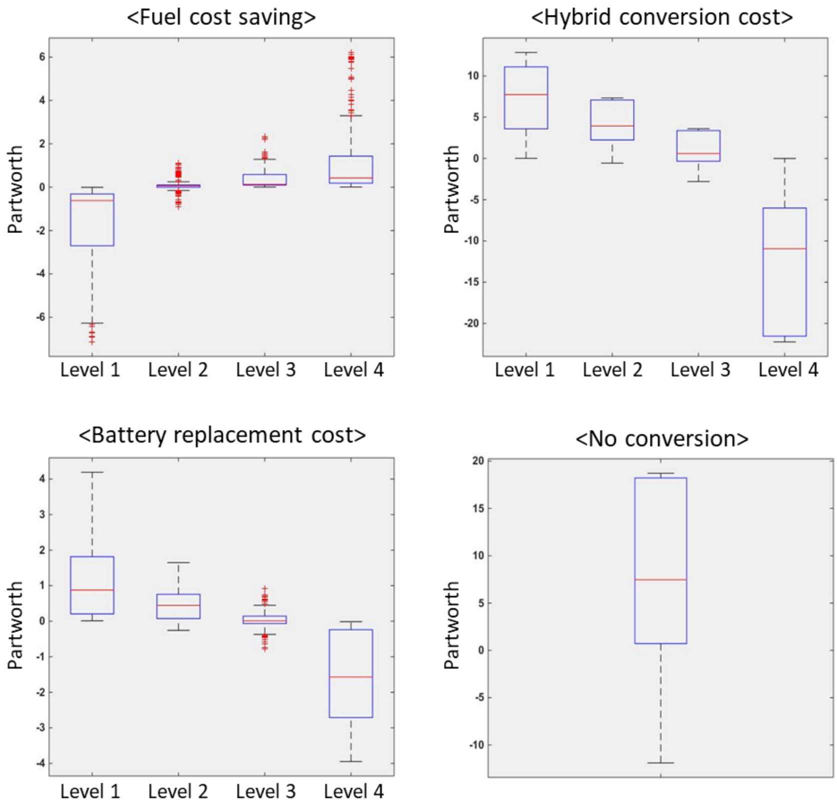
Note: The average values of partworth and importance of 191 respondents are presented, and their standard deviations are in parentheses. Partworths are the estimated β coefficients in equation (2) using the HB method. Importance is computed by the difference between the maximum and minimum partworths of each attribute divided by the sum of the differences between the maximum and minimum partworths of each attribute. Note that the importance in Table 3 is the average of the importance of 191 individuals for each attribute. KRW 10,000 was equal to approximately USD 8.85 as of 2017.

The table shows the partworth for the levels of each attribute (fuel cost saving, hybrid conversion cost, battery replacement cost), or the β_{ikl} of level l of attribute k averaged over individuals i's in equation (2). The partworth refers to the degree of preference for a level of a certain attribute, where a larger value indicates higher preference. The partworth is expressed in the same unit as total utility, and the total utility of a product can be calculated as the sum of the partworths of all its attribute levels. The highest partworth is at 7.03 when the hybrid conversion cost is KRW 1 million, and it falls sharply as the cost increases. It reaches the lowest at –11.90 when the conversion cost is KRW 6 million.

With the estimated values of partworths, the importance of each attribute can be calculated. The importance of an attribute is defined by the relative value of an attribute contributing to one's utility. The numerator of the importance measure is the difference between the maximum and minimum partworths of each attribute, while the denominator is the sum of the differences between the maximum and minimum partworths of each attribute. Therefore, the sum of the importance of each attribute adds up to 100%. The importance shown in Table 3 represents the averages and standard deviations of 191 respondents computed for each attribute. The importance for hybrid conversion cost computed is 69.1%, 21.0% for fuel cost savings, and 9.9% for battery maintenance cost.

Figure 3 illustrates the partworth analysis of 191 respondents by the level of each attribute in box plots. It graphically shows the ranges of the values by quartiles with the median indicated by the central line in each box. One can see that the distributions of partworths for each level are mostly skewed with different spreads. Since the distributions are not considered normal, when computing hybrid conversion probabilities below in Section 3.2, analyses in both mean and median values are conducted.

Figure 3. Box Plot for Attributes and their Levels of Hybrid Truck Conversion Technology



Note: The central line shows the median of the partworths. The bottom and top lines that border the box show the 25th and 75th percentile values, and the bottom and top whiskers indicate the minimum and maximum, respectively. Points beyond the minimum and maximum are outliers.

3.2 Probability of Choosing Conversion

The probability of choosing to convert to hybrid trucks is calculated using equation (3) and the results in Section 3.1. A respondent chooses between converting his truck to a hybrid from three different options of specifications presented (each with different levels of attributes), or keeping his truck as it is now. Table 4 summarizes the probability of conversion across different levels of hybrid conversion costs, fuel cost savings, and battery replacement costs. It shows four different cases with various levels of hybrid conversion costs, and for each case, the conversion probability for each combination of different levels of battery replacement cost (rows) and fuel cost savings (columns) are displayed. The probability can be analyzed with either its average or median value. The left values represent the median, and the right values represent the average probabilities of 191 respondents.

Table 4. Conversion Probability by Attribute Levels

Case i) Hybrid conversion cost of KRW 1 million

		Fuel cost savings							
		15%		20%		25%		30%	
		Median	Mean	Median	Mean	Median	Mean	Median	Mean
Battery replacement cost (unit: KRW 10,000)	35	38.8%	45.9%	81.3%	57.7%	83.0%	58.8%	88.0%	62.9%
	45	20.7%	41.5%	55.3%	52.8%	62.3%	54.0%	79.5%	58.6%
	55	12.5%	38.8%	47.7%	49.8%	49.9%	51.0%	74.2%	55.8%
	65	2.6%	33.2%	18.5%	40.6%	20.3%	41.8%	37.3%	47.5%

Case ii) Hybrid conversion cost of KRW 2.5 million

		Fuel cost savings							
		15%		20%		25%		30%	
		Median	Mean	Median	Mean	Median	Mean	Median	Mean
Battery replacement cost (unit: KRW 10,000)	35	0.7%	28.4%	6.2%	34.0%	7.8%	35.5%	21.5%	41.7%
	45	0.4%	27.4%	3.6%	32.3%	6.1%	33.5%	11.8%	39.6%
	55	0.3%	26.8%	2.4%	31.2%	3.4%	32.5%	10.4%	38.5%
	65	0.1%	25.4%	0.9%	28.6%	1.2%	29.5%	2.4%	34.4%

Case iii) Hybrid conversion cost of KRW 4.5 million

		Fuel cost savings							
		15%		20%		25%		30%	
		Median	Mean	Median	Mean	Median	Mean	Median	Mean
Battery replacement cost (unit: KRW 10,000)	35	0.0%	21.8%	0.1%	23.2%	0.1%	23.6%	0.5%	24.1%
	45	0.0%	21.4%	0.1%	22.6%	0.1%	23.0%	0.4%	23.4%
	55	0.0%	20.9%	0.0%	22.0%	0.1%	22.3%	0.3%	22.7%
	65	0.0%	20.2%	0.0%	21.3%	0.0%	21.5%	0.1%	21.7%

Case iv) Hybrid conversion cost of KRW 6 million

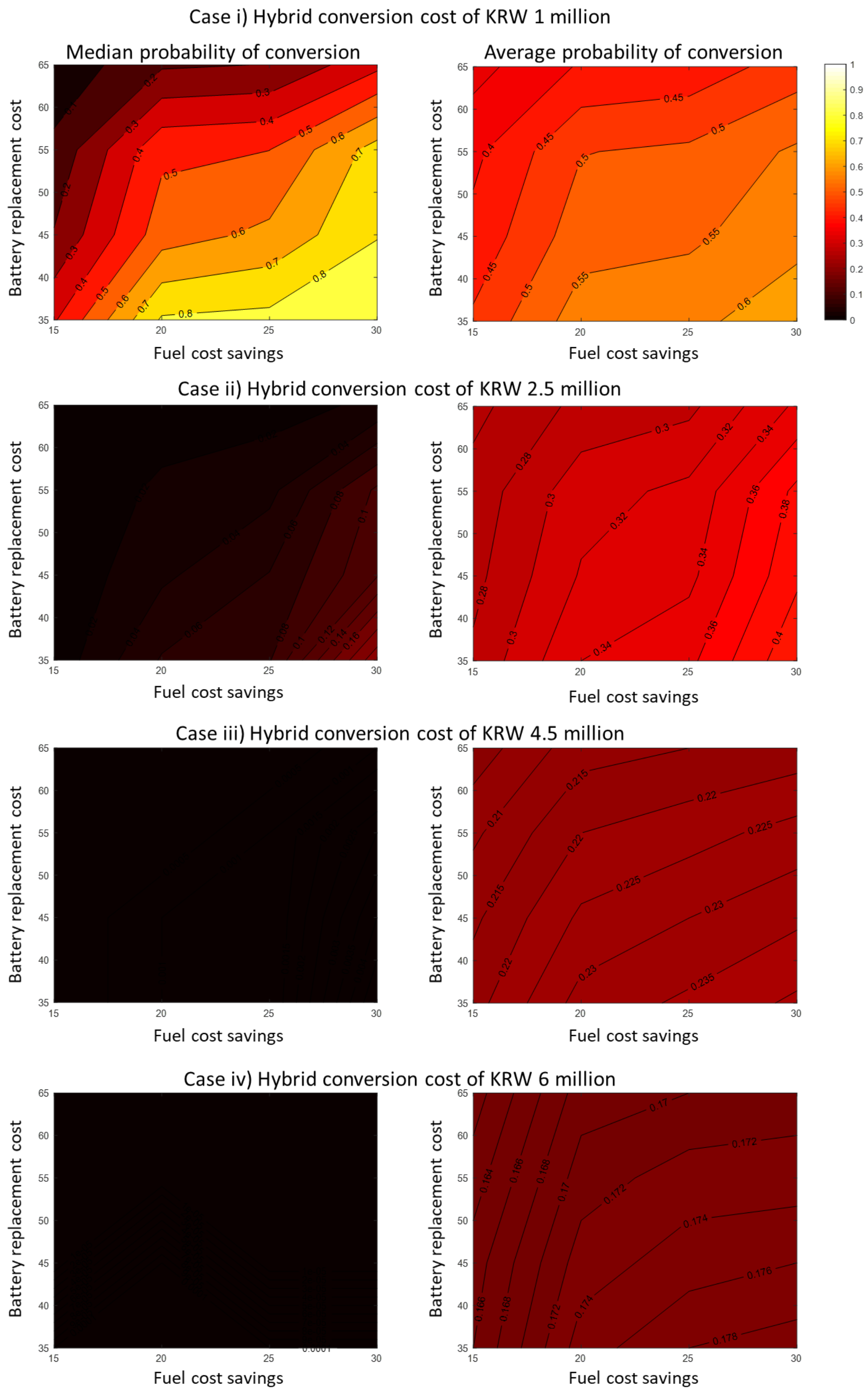
		Fuel cost savings							
		15%		20%		25%		30%	
		Median	Mean	Median	Mean	Median	Mean	Median	Mean
Battery replacement cost (unit: KRW 10,000)	35	0.0%	16.6%	0.0%	17.5%	0.0%	17.8%	0.0%	17.9%
	45	0.0%	16.5%	0.0%	17.3%	0.0%	17.5%	0.0%	17.6%
	55	0.0%	16.3%	0.0%	17.1%	0.0%	17.3%	0.0%	17.3%
	65	0.0%	16.1%	0.0%	16.9%	0.0%	17.0%	0.0%	17.1%

Note: KRW 10,000 was equal to approximately USD 8.85 as of 2017.

First, we examine the results based on the median conversion probabilities. Overall, the conversion probabilities are substantially higher when the hybrid conversion cost is KRW 1 million in Case i) than when it is KRW 2.5 million in Case ii). If the hybrid conversion cost is KRW 4.5 million or higher (Case iii) or iv)), the probabilities are closer to zero, and neither the fuel cost savings nor the battery replacement costs influences truck owners' choice of conversion much. Compared with the median values, the average conversion probability distribution is smoother, and the gap between the highest and the lowest probability is smaller. From the perspective of the hybrid conversion cost, the average conversion probabilities drop sharply when the cost increases from KRW 1 million (Case i)) to 2.5 million (Case ii)). When the conversion cost becomes KRW 2.5 million or higher, the probability decreases relatively gradually. As the hybrid conversion cost increases, the influence of fuel cost savings and battery replacement costs on the choice of conversion decreases more sharply.

Figure 4 advances the results presented in Table 4 in a continuous form with a Heat Map showing the conversion probabilities for combinations of different attribute levels. Cubic spline interpolation is performed to obtain continuous values of partworths across attribute levels, from which the conversion probabilities for continuous attribute levels are then obtained. Again, the cases are divided into four levels of hybrid conversion costs (Case i) to iv)). The lighter the shade, the higher the probability of conversion, and vice versa. The median conversion probabilities represented on the left column are zero if the hybrid conversion costs exceeds KRW 4.5 million regardless of the levels of the other two attributes, as shown by the shades that are completely dark in Case iii) and Case iv). There are still positive probabilities of conversion in terms of average values even as the conversion costs increase, as displayed on the right column. Figure 5 shows the relation between fuel cost savings and hybrid conversion costs when fixing the battery replacement cost to its minimum (KRW 350,000) and the maximum (KRW 650,000) separately. The results show that the median value of conversion probability is extremely low when the battery replacement cost is KRW 650,000, which implies that the market demand is also sensitive to maintenance costs as expected.

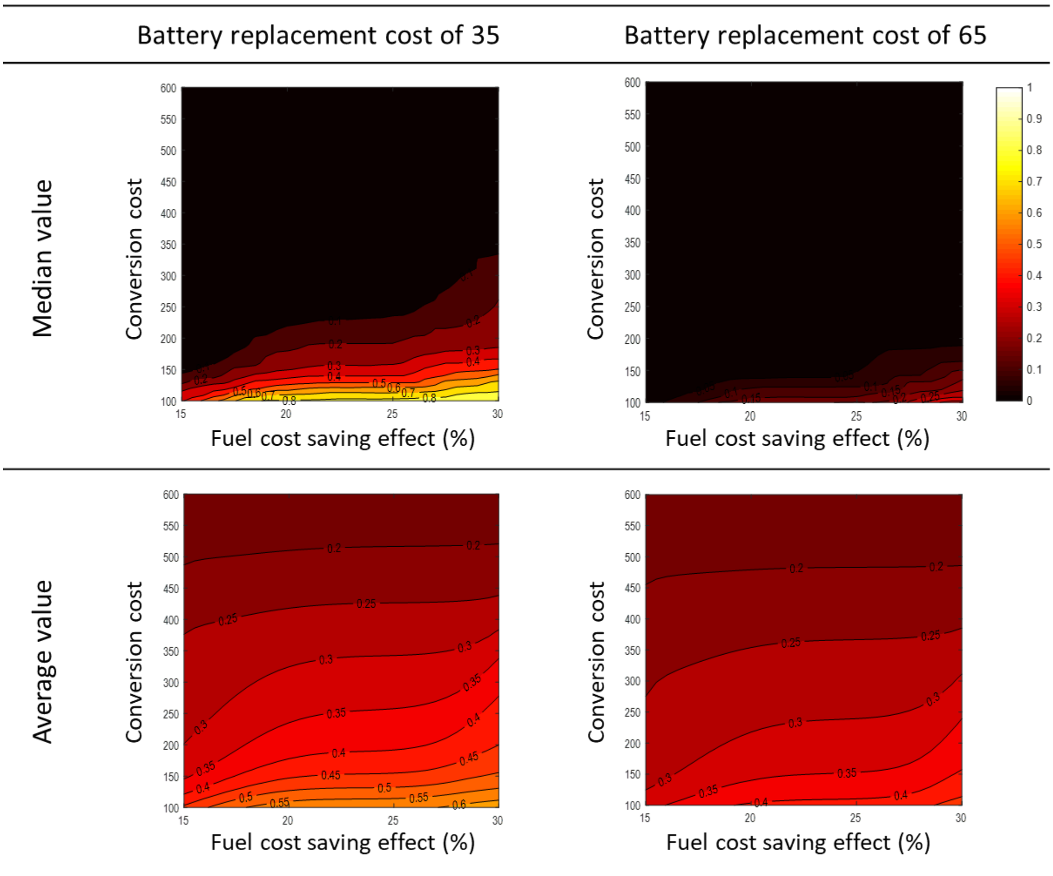
Figure 4. Heat Map of the Conversion Probability by Attribute Levels



Note: KRW 10,000 was equal to approximately USD 8.85 as of 2017
(Source: https://data.oecd.org/conversion/exchange-rates.htm).

Figure 5. Heat Map of the Conversion Probability by Battery Replacement Cost

(unit: KRW 10,000)



Note: KRW 10,000 was equal to approximately USD 8.85 as of 2017.

3.3 Willingness-to-pay (WTP)

In addition to their conversion probabilities, consumers' willingness-to-pay (WTP) for a unit of improvement for each level of attribute of a product can be obtained using the partworth values calculated from the HB analysis (Train, 2003, Kang et al., 2017b). Previously, the utility function was defined as a non-linear function of binary variables that indicate a level of an attribute and its partworths as in equation (2). When computing WTP, this equation is simplified by assigning one partworth value for an attribute instead of for all its levels, resulting in a linear functional form of utility. Here, each attribute - fuel cost savings, hybrid conversion cost, and battery replacement cost – would have one partworth utility coefficient. The HB estimation method is then applied to obtain the partworth estimates as before. This is done because the denominator when calculating WTP should be unified to a single value for ease of interpretation. WTP is then computed by dividing the partworth value of a product attribute by the price and switching the sign as in equation (4). Here, the price refers to hybrid conversion costs, i.e. one of the three attributes:

$$w_{ik} = -\frac{\beta_{ik}}{\beta_{ip}} \tag{4}$$

where w_{ik} denotes individual i's WTP for attribute k, β_{ik} indicates individual i's partworth value for attribute k, and β_{ip} is individual i's partworth value for the price, or hybrid conversion cost. A negative (-) sign is added because β_{ip} is always negative (the higher the price, the lower the value). This allows the sign or direction of WTP to be determined by the sign of the attribute on the numerator. w_{ik} denotes how much the individual is willing to pay to change a unit of attribute k. This is expressed as additional hybrid conversion cost that is incurred to improve attribute k that ultimately makes a consumer indifferent, or which brings about the same utility.

The WTP for improving one unit of fuel costs savings and battery replacement costs, respectively, is shown in Table 5. The median value of individual WTP, instead of the average value, of 191 respondents is used to estimate the WTP of the population. This is because the value of the cost coefficient that is close to zero (i.e., when consumers are not sensitive to price) results in an arbitrarily and erroneously large WTP (Orme, 2009). The results show that a median respondent is willing to pay KRW 289,000 more in conversion costs to increase fuel cost savings by 1%. In addition, he is willing to pay KRW 35,000 more for conversion to reduce KRW 10,000 of battery replacement costs.

Table 5. Calculating Willingness-to-Pay Conversion Cost by Attributes (Unit: KRW 10,000)

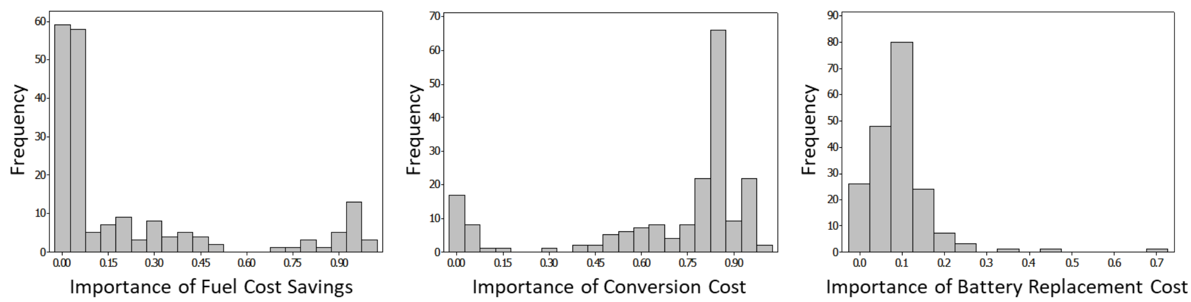
	Fuel cost savings (%)	Battery replacement cost (4-year cycle) (unit: KRW 10,000)
WTP (KRW 10,000)	28.9	-3.5

Note: KRW 10,000 was equal to approximately USD 8.85 as of 2017.

3.4 Consumer Classification by Attribute Importance

The importance of each attribute of the 191 respondents calculated in Section 3.1 is displayed as histograms in Figure 6. The distributions of the importance for fuel cost savings and hybrid conversion costs are polarized (i.e., either very important or very unimportant).

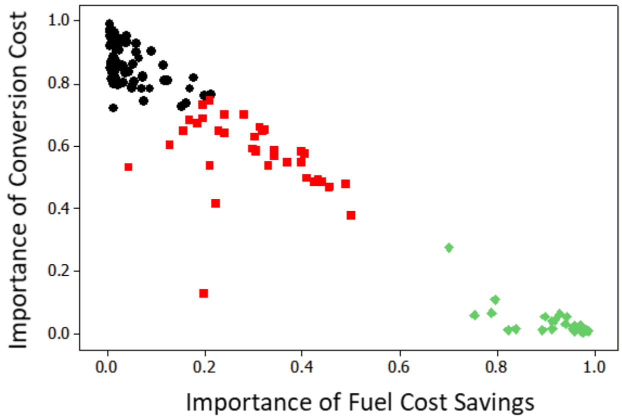
Figure 6. Histograms of Attributes Importance



In addition, the 191 respondents can be divided into three groups using the K-means clustering method by the importance of the effect of fuel cost savings (x-axis) and hybrid conversion costs (y-axis), as shown in Figure 7. These two attributes are selected for grouping since their distributions were polarized, whereas the distribution for battery replacement costs is not expected to affect consumer classification much based on results from Figure 6.

- Black: A group that thinks that hybrid conversion costs are very important – 129 respondents (68%)
- Red: A group that considers that hybrid conversion costs and fuel cost savings are equally balanced – 35 respondents (18%)
- Green: A group that thinks that fuel cost savings are very important – 27 respondents (14%)

Figure 7. Results of K-means Clustering by Attribute Importance (Three Groups)



The figure shows that most respondents consider hybrid conversion costs to be important, while the group that places importance on fuel cost savings only (Green) is distanced from the other two groups (Black and Red).

3.5 Demographic Factors Influencing the Importance of Product Attributes

Lastly, ordinary least squares (OLS) regression is conducted to determine which demographic characteristics influence the importance of attributes among individuals as calculated in Section 3.1. The demographic characteristics can be used to understand and explain the properties of consumer groups presented in the previous section. In the regression analysis, the dependent variable (Y) refers to the importance of the three attributes (fuel cost savings, hybrid conversion costs, battery replacement costs), and the independent variables (X) are defined as respondents' demographic characteristics. Table 6 presents the results of the regression analysis on each attribute. A total of 10 demographic characteristics are used. All variables are continuous except truck ownership, which is equal to 1 if the truck is owned by the truck owner's company and 0 if individually owned, and car type at purchase, which is equal to 1 if the truck was used at the date of purchase and 0 if it was new.

The regression analysis results are summarized as follows. The first column shows that consumers on average consider fuel cost savings to be more important if they are representatives of companies, the vehicle at purchase was new, the current mileage is higher, current fuel economy is lower, the average load weight is lighter, the parcel delivery work period is shorter, and the annual income is higher. Second, hybrid conversion costs are considered to be important, as the truck owner is self-employed, the vehicle is second hand, the current mileage is lower, the average load weight is heavier, the parcel delivery work period is longer, and the annual income is lower. The last column reveals that battery replacement costs are considered more important if the vehicle was used at the date of purchase and the average load weight is heavier.

Table 6. Demographic Characteristics Influencing the Importance of Attributes

	Importance of Fuel Cost Savings	Importance of Hybrid Conversion Costs	Importance of Battery Replacement Costs
Truck Ownership (Company or Individual)	0.30875**	-0.29833**	-0.01042
	(0.07382)	(0.07344)	(0.02217)
Model Year	0.00490	-0.00361	-0.00129
	(0.00882)	(0.00877)	(0.00265)
Car Type at Purchase (Used or New Car)	-0.1826**	0.14826**	0.03434*
	(0.05402)	(0.05374)	(0.01622)
Average Monthly Fuel Cost	0.00151	-0.00114	-0.00037
	(0.00152)	(0.00152)	(0.00046)
Current Mileage	0.00000116*	-0.000001*	0.00000
	(0.00000049)	(0.00000049)	(0.00000015)
Average Daily Mileage	-0.00117	0.00089	0.00028
	(0.00096)	(0.00096)	(0.00029)
Current Fuel Economy	-0.0301*	0.02188	0.00822
	(0.01472)	(0.01464)	(0.00442)
Average Load Weight	-0.07971**	0.06942**	0.01030*
	(0.01431)	(0.01423)	(0.00430)
Period of Working in Parcel Delivery Services	-0.00130**	0.00129**	0.00000
	(0.00037)	(0.00037)	(0.00011)
Annual Income	0.03018*	-0.03154*	0.00135
	(0.01235)	(0.01229)	(0.00371)

Note: The values are estimated coefficients from OLS regressions on importance of each attribute. Truck ownership is a bina ry variable equal to 1 if the truck is owned by the truck owner's company, and 0 otherwise. Car type at purchase is equal to 1 if the truck was used at the date of purchase and 0 if the truck was new. Standard errors are in parentheses. * p-value≤0.05, * * p-value≤0.01.

Table 7 summarizes these results showing only the sign, or direction of the relationship, and level of significance of the OLS coefficients. The table shows that demographic characteristics influence the importance of fuel cost savings and hybrid conversion costs in opposite directions. The factors that significantly influence the importance of both fuel cost savings and hybrid conversion costs are as follows: whether the truck owner is representative of a company or self-employed, whether the vehicle is used or new, the current mileage, the average load weight, the period of working in the parcel delivery service industry, and annual income.

Table 7. Demographic Characteristics and Importance of Attributes

Demographic Characteristics	Importance of Fuel Cost Savings	Importance of Hybrid Conversion Costs	Importance of Battery Replacement Costs
Truck Ownership (Company or Individual)	**+(**)**	**-(**)**	-
Model Year	+	-	-
Car Type at Purchase (Used or New Car)	**-(**)**	**+(**)**	**+(*)**
Average Monthly Fuel Cost	+	-	-
Current Mileage	**+(*)**	**-(*)**	-
Average Daily Mileage	-	+	+
Current Fuel Economy	**-(*)**	+	+
Average Load Weight	**-(**)**	**+(**)**	**+(*)**
Period of Working in Parcel Delivery Services	**-(**)**	**+(**)**	+
Annual Income	**+(*)**	**-(*)**	+

Note: The signs of the coefficients that are statistically significant from Table 6 are shown in the current table. The significan ce levels are denoted in parentheses where * p-value≤0.05, ** p-value≤0.01.

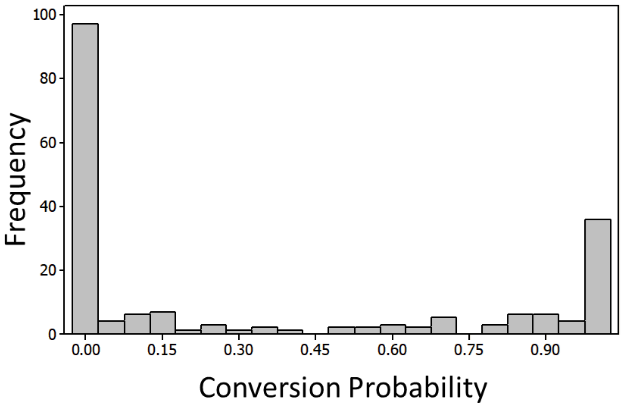
4. Discussion

This section presents insights by topic based on the results of Section 3 that can help a hybrid conversion R&D project manager in the process of decision making.

4.1 Heterogeneous Demand

This study modeled heterogeneous preferences using the HB method and derived an individual preference model for each of the 191 owners of parcel delivery trucks. As shown in Table 3, the standard deviation values of the partworth utility and importance are considered to be large, which indicates that there are considerable differences in preferences among consumers. Moreover, histograms of the importance of attributes in Figure 6 show that consumer preferences are polarized. And Table 4 listing the conversion probability reveals that there is a large gap between its median and average values. This is because consumer preferences are again polarized. As an example, the distribution of conversion probability, when the hybrid conversion cost is KRW 2.5 million, fuel cost savings is 30%, and battery replacement cost is KRW 650,000, is represented in Figure 8. According to this figure, the majority of respondents report a conversion probability of 0% or 100%, while the rest of the respondents are distributed equally in between these values. The average conversion probability of the 191 respondents is 34.4% while the median value is 2.4%. The findings reveal that preferences regarding hybrid truck conversion and conversion probability are heterogeneous, thus this needs to be taken into account for policy analyses.

Figure 8. Example of Conversion Probability Distribution



Note: KRW 10,000 was equal to approximately USD 8.85 as of 2017.

4.2 Accuracy of Demand Forecasting

To evaluate the accuracy of this model in a market with high degree of heterogeneity, the survey questions are divided into a train set and a test set to determine how accurately a model that learned from the train set can predict the test set. This is a widely used method to evaluate the accuracy of a conjoint analysis model. In this study, two questions out of a total of 15 were selected for testing, while the remaining 13 questions were selected for training. The test questions were converted from multiple-choice questions with four options to three binary questions for use in the test. First, to calculate the hit rate of the individual preference model, cross-validation was conducted to test every possible combination of the two test questions selected among the total of 15 ($\frac{15\times14}{2} = 120$ combinations) and to compute the average of hit rate. The average hit rate of the 191 respondents was 88.3%. As the test was conducted using binary questions, a completely random prediction would produce a 50% hit rate. The result of 88.3% thus indicates that the model in this study forecasts a heterogeneous market relatively accurately.

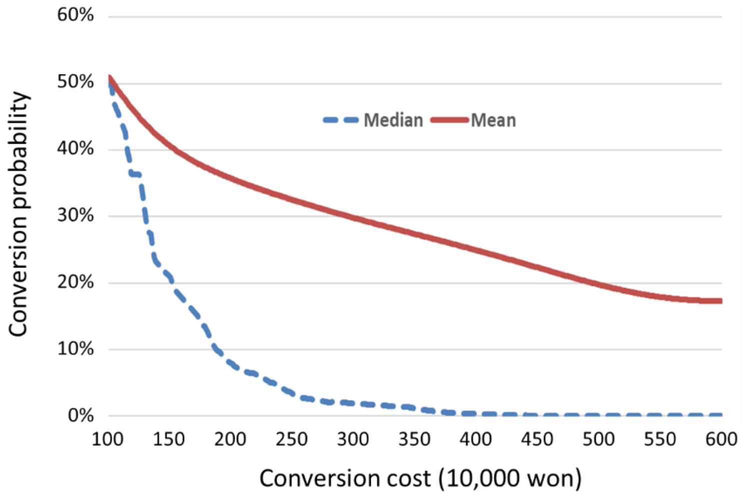
4.3 Differences between General Preference and Preference according to Conversion Attributes

At the end of the survey, we asked “Will you consider converting your parcel delivery truck to a hybrid?” This question was posed to simply determine the general preference of truck drivers without giving any information on vehicle attributes. In all, 28.8% of the subjects answered “Yes” to this question. With this general preference (28.8%) as the baseline, the conversion probability predicted in Table 4 using HB estimation can be compared to analyze the level of expected costs and vehicle performance that is needed for 28.8% of the respondents to convert to hybrids. In the table, analysis using the average values shows that when hybrid conversion costs are KRW 2.5 million or lower and fuel cost savings are 20% or higher, over 28.8% of respondents will choose to convert their trucks regardless of the battery replacement cost (i.e., all possible combinations of Case i) and the last three columns of Case ii)). Analysis using the median values shows that when the hybrid conversion cost is KRW 1 million, fuel cost savings is 20% or higher, and the battery replacement cost is KRW 550,000 or lower, more than 28.8% of respondents will prefer conversion (i.e., intersection of top three rows and last three columns of Case i)). On the other hand, when the hybrid conversion cost is KRW 2.5 million or higher (Case ii), iii), and iv)), the conversion probabilities do not reach 28.8%, and changes in other attributes do not influence the conversion probability substantially. This implies that hybrid conversion costs, fuel cost savings, and battery replacement costs should be balanced to satisfy general expectations of conversion, while improvement of other attributes does not have a significant impact when hybrid conversion costs go over a certain threshold.

4.4 Feasibility Test of the Hybrid Conversion Project

One of the main purposes of this study is to verify the feasibility of the government-led R&D project to convert parcel delivery trucks to hybrid vehicles. A pool of experts and research team involved in this government project have initially proposed a goal of fuel cost savings of 25% and battery replacement cost of KRW 550,000. It is worth noting that although the current study began with this target in mind and assessed the expected outcomes using the ranges around it, the realized fuel cost savings and battery replacement costs in the end may differ from the initial target values. The median and mean values of the conversion probabilities by hybrid conversion costs when the other two attributes are set to the target values are displayed in Figure 9. This is simply a continuous version of Table 4 but with fixing the fuel cost savings to 25% and battery replacement cost to KRW 550,000.

Figure 9. Conversion Probability according to the Hybrid Conversion Cost



Note: KRW 10,000 was equal to approximately USD 8.85 as of 2017.

Based on the mean values, only when the hybrid conversion cost is KRW 3.2 million or less, the conversion probability is above 28.8% which represents a general preference for conversion from survey results. Looking at the median values, the hybrid conversion cost should be KRW 1.31 million or less to reach the conversion probability of 28.8% or more. After setting developmental targets, it appears that the government ought to secure a budget to cover some conversion costs in order to elicit desired hybrid conversion decisions, and it may have to consider ways of providing subsidies to achieve its goals.

4.5 Offering Installment Payments for Hybrid Conversion Costs

One of the key insights regarding hybrid conversion costs is that consumers are sensitive to the fixed costs that they need to pay up front. Even if the savings in fuel costs will eventually exceed the payments paid for conversion in the long term, consumers tend to place more weight on current expenditures. This implies that there is a considerable psychological discount rate against future utility. On the preference for timing of payments of products, Patrick and Park (2006) reveals that consumers tend to prefer prepayments for purchases of nondurable goods that are especially associated with pleasure, or hedonic goods. On the other hand, consumers prefer to postpay for durable goods due to the time discounting that enables consumers to discount the cost of the good through its usage of it over time. Similarly, due to the benefits of hybrid vehicles that are reaped over time as a durable good and the existing uncertainties or risks involved regarding future maintenance costs of hybrid vehicles, consumers may prefer postpayment to prepayment. In fact, when asked why they would not consider hybrid conversion in the survey, the main factors that respondents mentioned were the possibility of technical failures and concerns on the power of hybrid vehicles. This problem can be addressed by government subsidies that would allow consumers to pay for hybrid conversion in installments instead of lump-sum prepayments. The introduction of such an installment plan will allow consumers to compare their installment payments with fuel cost savings each period, and is expected to reduce future uncertainties surrounding conversion.

In addition, Section 3.3 discussed the results regarding consumers' WTP for improving hybrid technology. The results showed that to reduce battery replacement costs by another KRW 10,000, consumers would be willing to pay an additional KRW 35,000 for conversion. Both battery replacement and hybrid conversion costs are translated in monetary terms, but the former is generated every fourth year after conversion. Thus, consumers will discount the monetary value that will be spent in the future. Policymakers need to understand this tendency among consumers and thus formulate polices to allow them to divide such costs and make installment payments.

4.6 Strategy of Focusing on Target Consumer Segments

This study shows the need to identify consumer segment targets for hybrid truck conversion and to primarily focus marketing resources on them. The findings of the research confirm that consumers have heterogeneous preferences regarding the conversion of trucks to hybrid vehicles. There are a few takeaways from the results. (1) According to the consumer classification of attribute importance in Figure 7, 129 consumers (68%) who prioritize conversion costs and 27 consumers (14%) who stress fuel cost savings are distributed at the two extremes. Consumers with conversion intentions are more likely to consider fuel cost savings to be more important, thus it is important to target this consumer segment in order to promote hybrid conversion. (2) In Section 3.5, the examination of demographic characteristics showed that those who place priority on fuel cost savings tend to be representatives of companies rather than self-employed. This result seems to have been observed because company representatives are relatively less sensitive to hybrid conversion costs relative to the self-employed, and are more likely to consider overall profits obtained through fuel cost savings. In addition, those with higher annual income regard hybrid conversion costs to be less important and place more emphasis on fuel cost savings. (3) The respondents were found to be more sensitive to conversion costs when they had purchased a second-hand truck because they were less willing to make additional investments in the vehicle. (4) Those with vehicles with relatively light average load weight and low fuel economy considered fuel cost savings to be important. It can be assumed that those with vehicles with high average load weight should have negative views about conversion given the low power expected of hybrid vehicles, as many respondents noted “low power” as a disadvantage of hybrid conversion. On the other hand, those who recently started working in the parcel delivery service industry tended to be more positive about hybrid conversion and the fuel cost savings that it can bring. In conclusion, strategies to focus on a pool of target consumers are necessary, after which the policy can then reach out to a wider range of consumers.

5. Conclusion and Policy Implications

The Korean government is planning an R&D project to convert the existing diesel trucks to diesel-electric hybrid vehicles in order to reduce PM and greenhouse gas emissions from parcel delivery trucks. This study examined the marketability and economic feasibility of hybrid conversion as part of the planning stages of a larger R&D project by modeling preferences of diesel truck owners. To this end, HB choice-based conjoint analysis was used to conduct the following tasks: calculate the importance of conversion attributes, forecast the conversion probabilities by attribute levels, calculate consumers’ WTP, classify consumers by attribute importance, and analyze demographic factors influencing each attribute importance.

The analysis results provided a range of insights into the R&D project for decision makers. First, consumers have heterogeneous preferences and are particularly sensitive to hybrid conversion costs, thus it is necessary to set an optimal conversion cost by considering both the technological feasibility and returns to government investment through the demand forecasting model. In addition, policies that allow consumers to pay in installments for the conversion so that they can compare the gains from fuel cost savings each period must be formulated, instead of having them pay for the full cost in a lump sum. Finally, it is necessary to first focus on the consumer segment target that prioritizes fuel cost savings before gradually expanding to a larger consumer base.

Although the reliability of data may decrease when respondents lack concentration during the survey and when consumer preferences regarding conversion are too heterogeneous to be represented by a mean or median value, the study is meaningful in that it is one the first few papers to examine consumer preferences on vehicle conversion. The current analysis considered consumer preferences only, but forthcoming research should integrate government budget and material costs required by attribute enhancements to offer a more balanced approach for setting development goals and devising subsidy policies to achieve maximum conversion probability and returns on investment (Kang et al., 2016). Moreover, analyses should be conducted to consider the relationship between consumer preferences and technical feasibility while evaluating engineering performance (Kang et al., 2015, 2017a). These types of analyses would provide a more a holistic insight on project development.

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