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Studies on Heterogeneous Decision-Making Structure in terms of Attribute Non-Attendance and Random Regret Model

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Abstract

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Understanding consumer taste heterogeneity is always a crucial part of establishing marketing activities. The distributional approaches of consumer preferences have played an important role in statistical marketing applications. These statistical approaches have evolved in various ways, and this dissertation adds diversity to the field of consumer heterogeneity studies. This study proposes a series of models that capture consumer heterogeneous decision-making strategies as a perspective of consumer heuristic behavior by adopting a Bayesian stochastic search variable selection model. The proposed models in this dissertation are two fold. First, this study suggests a model for explaining consumers' attribute non-attendance behavior with consumer characteristics. When consumers face complex decision-making situations, they are possibly

attracted to or ignore one or more attributes while processing the information on offer, which cannot be explained with the usual random utility maximization model. Previous studies attempt to explain this attribute non-attendance behavior by questioning respondents directly or stochastically estimating a considered subset. However, these models do not explain the relationship between consumer non-attendance behavior and individual characteristics. This dissertation suggests a method for capturing respondents attribute non-attendance behavior based on their individual socio-demographic characteristics. Second, distinguishing agents' decision-making strategies is also a critical issue for understanding consumer heterogeneity. Previous research suggests various alternative decision-making strategies and demonstrates consumer decision-making strategy with the latent class model or with comparison of model fit measures such as Akaike Information Criteria or Bayesian Information Criteria. These approaches may possibly classify consumer decision-making strategies but they do not fully identify individual heterogeneity for individual decision-making strategy. Among suggested alternative decision strategies, this dissertation focuses on random regret minimization, which is conceptually opposite to random utility maximization. This dissertation proposes a model for identifying individual decision-making behavior heterogeneity between random utility maximization and random regret minimization using the Bayesian stochastic search methods.

The empirical analysis was conducted with three high-tech durable goods: a

zero-energy house, a telecommunications bundle, and a vehicle choice behavior. High-tech durable goods were chosen for empirical analysis because high-tech durable goods have many attributes in comparison with other goods categories, and therefore, respondents face complex, uncertain decision-making situations while decision making process. The empirical results illustrated these attribute non-attendance and complex decision-making behaviors well.

The suggested model in this dissertation has two main implications. First, from the perspective of the new product design process, manufacturers in the product planning stage should identify consumer consideration of product attributes. Next, setting up a marketing strategy based on segmentation, targeting, and positioning require classification of consumer characteristics based on consumer choices. The models suggested in this dissertation effectively organize consumer heterogeneity with reference to consumer socio-demographic traits.

Keywords: Discrete Choice Model; Heterogeneous Heuristic Decision-Making structure; Attribute Non-Attendance; Random Regret; Bayesian Estimation; Stochastic Search Variable Selection

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Chapter 1. Introduction

1.1 Research Background

Over the past two decades, the discrete choice experiment has contributed remarkably to the understanding of consumer behavior. A tremendous number of discrete choice studies have been executed in academia. The center of interest in the discrete choice experiment is to derive the heterogeneity of consumers. Understanding consumer heterogeneity has long been a critical issue in several fields where people's behavior needs to be understood, such as transportation and energy, marketing, environmental studies, labor, and health (K. Train, 2009).

Understanding consumer heterogeneity cannot be emphasized enough especially in high-tech marketing fields. The most fundamental step in innovative high-tech marketing is to identify consumer needs. The creation of consumer needs is as important as identifying consumer dissatisfaction and frustration. Individual needs are created when a situation arises where an individual's desire transcends his/her reality. Innovation can be created by consumers' needs (demand-driven) or by stimulating consumers' needs through the introduction of new products. Then, the individual's adoption of high-tech goods begins when these needs are met. (Rogers, 1995)

To place high-tech goods in the market successfully, companies must exceed

critical mass. The most important thing to reach the critical mass is identifying which individuals are accepting brand-new goods with uncertainty before popularized. The taste and threshold for adopting high-tech goods are various among the individuals in the market. Due to this heterogeneity, diffusion takes place in the form of S-shaped curves. Therefore, understanding consumers' taste and their threshold has been the most critical concern in high-tech marketing.

Growth Era	**Mass Market**	**Segment**	**Customer**	**Loyalty**	**Relevance**
Decade	1960s~1970s	1980s	1990s	2010s	2020s
Technology enabler	Mass production	Market research	Enterprise IT	Advanced CRM	Digitization of everything
Performance indicator	Volume	Purchase funnel	Customer lifetime value	Customer retention	Customer attraction
Market approach	Mass appeals	Segmentation	Proposition innovation	Tailored incentives	Personalization
Management focus	Product and scale	Channel and scale	Channel and relationship	Experience and relationship	Experience and personality

Figure 1. How Marketing Moved from the Mass-Market to Relevance (HBR, 2018)

High-tech marketing paradigms evolved from market-level to individual-level gradually (Figure 1). At first, in the mass-market level, marketing was mainly implemented via mass media, such as the radio, television advertisements, and leaflets, in an undifferentiated manner. Subsequently, marketers have begun to understand the diffusion of innovation and how to set aside critical mass to

successfully diffuse high-tech goods. They have begun to develop strategies to respond to customer heterogeneity by dividing customers into segments. Recently, with advances in information technology, marketing techniques have become more and more delicate. Marketing has evolved to a personal level, and therefore, marketers must understand the characteristics of consumers at an individual level. In the US market alone, companies were losing trillions of dollars to their competitors because their marketing strategies were not relevant enough (John, Wollan, & Bellin, 2018). Therefore, understanding consumers at the individual level is essential for the successful proliferation of products.

Mainly, consumer heterogeneity has been dealt with using distributional approaches. The heterogeneity of consumers can be understood through the stochastic terms in utility coefficients, assuming that the utility of respondents is likewise influenced by the stochastic terms and has different values in utility coefficients grouped with individuals that have same choice behavior (mixed logit) or similar individual characteristics (latent class logit) or both (hierarchical Bayes (HB) logit with covariates). These statistical approaches usually assume that the individual decision-making structure is linear-additive and they assume the continuity axiom, which also refers to unlimited substitutability. In other words, all the attributes suggested in the choice situation have unlimited substitutability, and respondents make trade-offs between all the presented attributes describing each of the alternatives. The continuity axiom has long been

a basis for choice modeling. Most scholars have accepted the continuity axiom without doubt and have focused solely on heterogeneities in linear additive models. (C. G. Chorus, 2014a)

However, researchers obtain experimental results that do not support the rational decision-making behavior of respondents, such as asymmetric reaction toward exposed risks or benefits, which are usually noted as decision heuristics (A Tversky & Kahneman, 1974). These experimental studies imply that decision-makers are not always rational, and they show irrational decision-making behavior in particular circumstances such as risky choice situations where they may suffer regret from their decision. Therefore, researchers have suggested alternative decision-making structures based on psychology and behavioral economics in consumer research.

This study focused on two representative alternative decision-making concepts, attribute non-attendance (ANA) and the hybrid structure of random utility maximization and Random Regret Minimization (Hybrid RUM-RRM). ANA, an idea that has received much interest in alternative decision-making structure, implies that some attributes presented in a choice situation are ignored by respondents because of the complexity of the choice situation or the respondents' biased choice behavior. Therefore, the ignored attributes are latently removed from the decision-makers' utility structures.

These two concepts have attracted much research and are essential in

comparison with other alternative decision rules. First, they are quite parsimonious than other alternative decision rules. (Hess, Beck, & Chorus, 2014) ANA removes attributes that are not engaged in the decision-making process (R. Scarpa, Zanoli, Bruschi, & Naspetti, 2013). The random regret model, which is somewhat more complicated than ANA, captures semi-compensatory decision rules in a choice situation in a simplified reference-dependent manner. Second, they both have the characteristic of formal tractability. Last, they have the advantage of being able to classify decision structures by attributes separately. Therefore, this dissertation focused on the heterogeneous decision-making structure of respondents from the ANA and hybrid RUM-RRM formation perspectives (C. G. Chorus, Rose, & Hensher, 2013).

Not only accounting for taste heterogeneity, this dissertation also proposed a series of models that capture consumer heterogeneous decision-making strategies from the perspective of consumers' heuristic behavior by adopting a Bayesian stochastic search variable selection model. The suggested methodology expands the current statistical approaches to incorporate heterogeneous decision-making strategies at the individual level and adds diversity to the field of consumer heterogeneity studies.

1.2 Research Objectives

The research objective of this dissertation is to propose new methods for understanding consumer heterogeneity. Not only does it cope with utility heterogeneity at the individual level of respondents, but it also deals with respondents' heterogeneous decision-making structure.

This dissertation suggests a model for explaining the ANA behavior of consumers taking consumer characteristics into consideration. When consumers face complex decision-making situations, they are possibly attracted to or ignore one or more attributes while processing the information on offer, which cannot be explained by the usual random utility maximization model. Previous studies attempt to explain this ANA behavior by questioning respondents directly (stated attendance) or stochastically estimating a considered subset (latently estimated attendance). However, these models have failed to explain the relationship between consumer non-attendance behavior and individual characteristics. This dissertation suggests a method for describing the respondents' ANA behavior based on their individual socio-demographic characteristics. Second, distinguishing agents' decision-making strategies is also an essential component of understanding consumer heterogeneity. Previous studies suggest various alternative decision strategies and demonstrate consumer decision-making strategy with the latent class model or comparison of model fit measures such as Akaike Information Criteria or Bayesian Information Criteria. These approaches may possibly classify consumer decision-making strategies, but they do not fully

identify individual heterogeneity for individual decision-making strategies. Among the suggested alternative decision strategies, this dissertation focuses on random regret minimization, which is conceptually opposite to random utility maximization. This dissertation proposes a model for identifying individual decision-making behavior heterogeneity between random utility maximization and random regret minimization via Bayesian stochastic search methods.

1.3 Research Outline

The dissertation is organized into five chapters as follows: Chapter 2 covers the theoretical background of this study with a review of previous literature related to its main subjects: discrete choice models, stochastic search variable selection and heterogeneous variable selection, and alternative decision-making rules, which focus on attribute-processing behavior and the random regret model. At the end of chapter 2, previous studies' limitations and methods for overcoming them are discussed. Chapter 3 proposes two methodologies: A heterogeneous variable selection choice model with respondent covariates (HVSC) and a heterogeneous choice model for respondent decision heuristics strategy. The last section of Chapter 3 reports the simulation results of the proposed models with synthetic data. Chapter 4 discusses the empirical application of the proposed models, including high-tech goods and service: consumer preference for zero

energy houses, bundling behavior of Telecommunications, and vehicle choice behavior. Chapter 5 summarizes the implications and limitations of this study and proposes future research directions.

Chapter 2. Literature Review

This chapter overviews previous literatures about the main subject of this dissertation: discrete choice model and its expansion, stochastic search variable selection model, decision heuristics in choice models and Bayesian inference algorithm.

2.1 Discrete Choice Models

Discrete choice model has been used in various field such as environment, marketing, policy, and so forth. Discrete choice model statistically estimates consumer preference via decision-makers' choices among a set of alternatives. Decision-makers, the base unit of the analysis, can be individual decision-making units, such as people, households, firms, etc. To exhibit decision-makers' utility, a researcher observes decision-makers' choice among a set of alternatives and analyzes the collected data with a logit or probit based model. This section focuses on discrete choice models and other models that reflect respondents' heterogeneity.

2.1.1 Multinomial Logit Model

Choice models use a variety of consumer choice observation, including single choice, multiple-choice, rank-ordered, rating, and continuous-multiple usage. Depending on the data, different choice models or different distributional assumption can be applied. Among those models, this section mainly reviews single choice among multiple alternatives in a choice situation, multinomial logit model, or conditional logit.

The choice models are based on the random utility model (McFadden, 1974). When a decision-maker *i* chooses the alternative *j* in choice situation *t*, the utility of a decision-maker *i* is shown as in Eq. (2.1). Utility is consisted of two parts; V_{itj} represents the deterministic part of the utility and ε_{itj} represents stochastic part of the utility. Usually, the deterministic part consists of a linear combination of attributes, which assumes that respondents are rational human being and therefore, respondents choose to maximize his/her utility. However, the form of deterministic part can be replaced by alternative decision-making rules, which are covered in section 2.3.

$$U_{itj} = V_{itj} + \varepsilon_{itj} \qquad \text{Eq. (2.1)}$$

The unobservable part of the utility ε_{itj} follows extreme value distribution or type-I Extreme value distribution in the logit model, and cumulative normal distribution in the probit model (K. Train, 2009). In the logit model, each ε_{itj} is assumed to be independent, identically distributed (i.i.d.) extreme value distribution. The density of unobserved part of utility can be represented as in Eq. (2.2), and the cumulative distribution as in Eq. (2.3).

$$f\left(\varepsilon_{itj}\right)=\exp\left(-\varepsilon_{itj}\right)\exp\left(-\exp\left(-\varepsilon_{itj}\right)\right) \qquad \text{Eq. (2.2)}$$

$$F\left(\varepsilon_{itj}\right)=\exp\left(-\exp\left(-\varepsilon_{itj}\right)\right) \qquad \text{Eq. (2.3)}$$

Assuming that a respondent chooses an alternative which maximizes his/her utility among the choice set, the choice probability that decision-maker *i* chooses alternative *j* is shiwn in Eq. (2.4), as suggested in McFadden (1974).

$$\begin{aligned} P_{itj} &= \text{Prob}\left(V_{itj}+\varepsilon_{itj} > V_{itm}+\varepsilon_{itm}, {}^{\forall} m \neq j\right) \\ &= \text{Prob}\left(\varepsilon_{itm} > \varepsilon_{itj}+V_{itj}-V_{itm}, {}^{\forall} m \neq j\right) \\ &= \int\left(\prod_{m\neq j}\exp\left(-\exp\left(-\left(\varepsilon_{itj}+V_{itj}-V_{itm}\right)\right)\right)\right)e^{-\varepsilon_{itj}}e^{-\exp\left(\varepsilon_{itj}\right)}d\varepsilon_{itj} \\ &= \exp\left(V_{itj}\right)\Big/\sum_{m}\exp\left(V_{itm}\right) \end{aligned} \qquad \text{Eq. (2.4)}$$

Assume that respondents' choice in the choice situation is independent, the likelihood of respondent i is shown in Eq. (2.5). Also, assuming that each respondents' choice is independent among all respondents, the likelihood of the sample is shown in Eq. (2.6)

$$P_i = \prod_t \prod_j \left(P_{itj}\right)^{y_{itj}} \qquad \text{Eq. (2.5)}$$

$$L = \prod_i P_i = \prod_i \prod_t \prod_j \left(P_{itj}\right)^{y_{itj}} \qquad \text{Eq. (2.6)}$$

The variance of the above extreme value distribution [Eq. (2.2)] is $\pi^2/6$. In general, the error term has a variance of $\sigma^2 \times \left(\pi^2/6\right)$, and therefore, utility becomes $U_{itj} = V_{itj}/\sigma + \varepsilon_{itj}$. σ is called a scale parameter of utility, which does not matter when differences in utility are compared. If the error term has small variance, then the utility may be estimated larger/smaller than the researcher's expectation. Otherwise, the error term has a large variance, and vice versa. However, Train (2009) mentioned that the issue of variance in choice models could be summarized in two statements: "only differences in utility matter" and "the scale of utility is arbitrary". These phrases imply that absolute level of utility is irrelevant to both respondents' behavior and the researcher's model. To deal

with scale heterogeneity over subpopulation, Fiebig, Keane, Louviere, and Wasi (2010) suggest a model for estimating individual scale heterogeneity in a mixed logit model, which is called generalized multinomial mixed logit model. However, this dissertation does not reflect scale heterogeneity and scale of utility because the scale of variance is not considered. Also, there is a contradicting argument that individual scale heterogeneity is not necessarily controlled because well defined mixed logit specification already controlled individual scale heterogeneity (Hess & Rose, 2012).

The conventional linear additive logit exhibits a property of independence from irrelevant alternatives (IIA), which means that the ratio of alternative probabilities does not depend on other available alternatives. However, IIA property is unrealistic in many real-world settings. Also, in some alternative decision-making rule models, since decision-making rule depends on other alternatives such as random regret model or relative advantage model, those models lose IIA property.

In most cases, conventional logit model does not take into account respondents' taste variation in a model since it assumes point estimation of preference parameters. However, in the real world situation, the taste of consumers varies, and therefore, the estimation coefficients that cannot reflect heterogeneity in the logit model may be biased (Bhat, 1997). The discrete choice model was developed to further analyzing preference heterogeneity. Following

section reviews consumer heterogeneity in the choice model.

2.1.2 Consumer Heterogeneity in Choice Model

The choice model considering consumer heterogeneity includes the distributional terms in the utility parameters. Representative models of this approach are latent class logit and mixed logit model.

The latent class logit model estimates the preference heterogeneity of consumers by each segment (Kamakura & Russell, 1989). In other words, the latent class logit model assumes that preference coefficients follow a finite mixture of discrete point mass distribution (Allenby & Rossi, 1999). It assumes that the population is divided into Q number of groups, and consumers in the same group have the same preference toward attributes. The utility of decision-maker *i*, belonging to group *q*, choosing alternative *j* under choice situation *t* is shown in Eq. (2.7), where $V_{ijt|q}$ is the deterministic part and ε_{ijt} is stochastic part of the utility, which follows type-I extreme value distribution. The choice probability of consumer *i* is in Eq. (2.8)

$$U_{itj|q} = V_{itj|q} + \varepsilon_{itj|q} = \mathbf{X}_{itj}\boldsymbol{\beta}_q + \varepsilon_{itj|q} \qquad \text{Eq. (2.7)}$$

$$P_{i|q} = \prod_t \frac{\exp\left(V_{itj}\right)}{\sum_k \exp\left(V_{itk}\right)} \qquad \text{Eq. (2.8)}$$

In the common latent class model, membership probability is assumed to take the form of multinomial logit, but also use Dirichlet distribution for membership probability. The probability of respondent *i* belonging to group *q* is s_{iq}, then s_{iq} is interpreted as the weight on finite mixture coefficients. Respondent *i*'s choice probability of latent class logit model with multinomial logit membership is expressed as Eq. (2.9).

$$\begin{aligned} P_i &= \sum_Q s_{iq} P_{i|q} \\ &= \sum_Q \frac{\exp\left(Z_i \theta_q\right)}{\sum_Q \exp\left(Z_i \theta_{q'}\right)} \left(\prod_t \frac{\exp\left(V_{ijt|q}\right)}{\sum_k \exp\left(V_{ikt|q}\right)} \right) \end{aligned} \qquad \text{Eq. (2.9)}$$

The latent class model can divide the population with preference heterogeneity at the segment level, which the number of classes is pre-assigned by the researcher. Also, latent class logit model, which has a semiparametric specification, does not need distributional assumption about individual heterogeneity. However, compared to the mixed logit model, which has a fully parametric specification, latent class logit model has its limitation in flexibility.

Mixed logit model, which is a highly flexible model with the assumption of random taste variation, overcomes the three main limitations of standard logit model: allowing random taste variation, unrestricted substitution patterns, and correlation in unobserved factors (Train, 2003). Early application of individual-level data such as Train, McFadden, and Ben-Akiva (1987) only includes one or two dimensions of random taste variation. Improvement in computer speed has allowed the full dimension of random taste variation, which suggested in Train (1999).

As mentioned above, mixed logit assumed that random taste variation, which implies that the parameters in the model have distribution. Mixed logit probabilities can be expressed in Eq. (2.10), where $L_{ij}(\beta)$ is the logit probability at β and $f(\beta)$ is a density function of β and θ is a parameter that determines the shape of the distribution f.

$$P_{ij} = \int L_{ij}(\beta) f(\beta \mid \theta) d\beta \qquad \text{Eq. (2.10)}$$

Mixed logit probability is a weighted average of the logit formula, called mixed function, and the density of β is called mixing distribution. Researchers can consider the latent class model as a particular case of the mixed logit model, which mixing distribution is assumed as a finite mixture of point mass density.

The parameters β are integrated out, and what researcher estimates are random parameters θ. The researcher can specify a variety of distributions for the coefficients: normal, lognormal, truncated normal and triangular distribution, and so forth. Most cases use normal or lognormal distribution: i.e., $\beta \sim N(b,W)$ or $\ln\beta \sim N(b,W)$. Notably, the lognormal distribution is frequently assumed when the coefficient is known to have the same direction for all respondents, such as the cost coefficient. Since the coefficients in mixed logit allow covariance structure in the coefficients, mixed logit model relieves IIA assumption, and various correlation patterns can be obtained from the mixed logit model. Extending from the mixed logit models, normal mixture logit model is suggested for continuous multimodal heterogeneity (Allenby, Arora, & Ginter, 1998). Normal mixture logit models assume the preference parameters as a mixture of the normal distribution as shown in Eq. (2.11), which shows more flexibility, compared to conventional mixed logit model. π_q is a weight on the normal distribution $N(b_q,W_q)$, which is Dirichlet distribution in most cases.

$$\beta_i \sim \sum_q \pi_q N(b_q,W_q) \qquad \text{Eq. (2.11)}$$

The Bayesian estimation of choice model is firstly introduced by Albert and

Chib (1993), estimating multinomial logit and binomial logit model, and normally distributed coefficients mixed logit model is suggested by Allenby and Lenk (1994). Moreover, Train (2001) summarized the frequently used current mixed logit form with Bayesian procedure, especially with Gibbs sampling method. Mixed logit with Bayesian procedure uses hierarchical Bayesian concepts. Assuming that covariance matrix of coefficients (W) and mean of coefficients (b) is specified (usually a flat prior on b), the joint posterior on β_i is shown in Eq. (2.12)

$$\Lambda\left(\beta_i, b, W \mid Y\right) \propto \prod_i \left(L\left(y_i \mid \beta_i\right) g\left(\beta \mid b, W\right) IG\left(W\right)\right) \qquad \text{Eq. (2.12)}$$

Information about the posterior is drawn through a simulation process such as Gibbs sampling. Draws are taken sequentially from the previously drawn parameters excluding drawing parameter, and then the chain of draws from the conditional posterior converges to draws from the joint posterior.

The Bayesian procedures have two strengths compared to the standard maximum likelihood estimation procedure (Train, 2001). First, the Bayesian procedure does not require maximization of any function, which implies that the Bayesian procedure has numerically simplified calculation procedure, and can avoid falling into local maxima. Second, Bayesian estimation sets aside consistency and efficiency, which is the desired property of statistical estimation.

2.2 Stochastic Search Variable Selection Model

Stochastic Search Variable Selection model (hereafter “SSVS model”) was first suggested by George and McCulloch (1993). Before the SSVS model, similar setups were suggested in the variable selection context: Stewart (1987) and Stewart and Davis (1986) suggest Hierarchical Bayesian discrete distribution with many possible models (about variable selection), and Mitchell and Beauchamp (1988) used Spike-and-Slap mixture prior, which implies spikes in zero and slaps for estimating values. Other than Hierarchical Bayesian approaches, least absolute shrinkage and selection operator (LASSO) method, which uses L1 regularization methods to select features among candidates, is suggested by Santona and Symes (1986) and popularized by Tibshirani (1996). The critical concentration of those studies was to develop a procedure to select promising subsets among candidates of explanatory variables for further consideration.

When the number of explanatory variables is K, to avoid calculating 2^K models posterior probability, SSVS uses the Gibbs sampler to consider all the possible 2^K combinations of variables. Such variable selection models identify promising subsets of predictors with higher posterior probability, which has similar optimization concepts with Genetic algorithm (Holland, 1975).

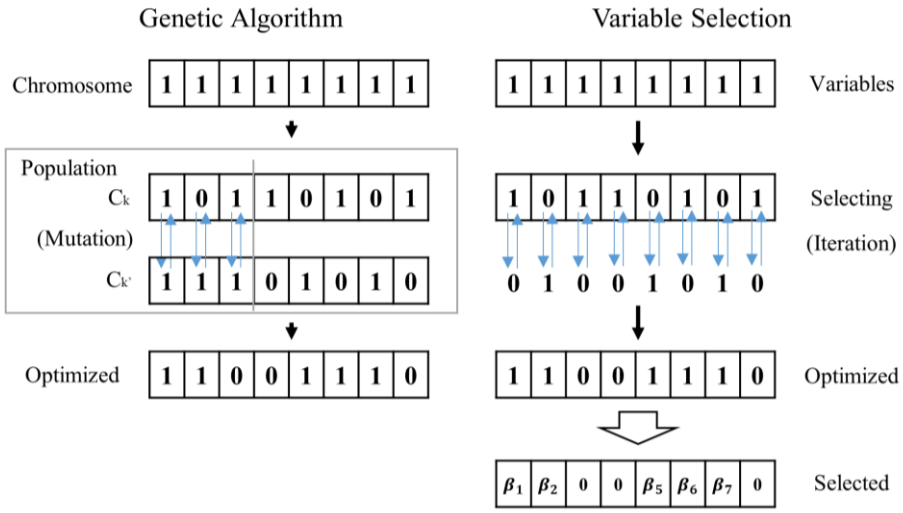


Figure 2. Diagram of Genetic Algorithm and Variable Selection

The possible 2^K combination of subset choices can be represented as Eq. (2.13) where $\gamma_k = 0$ if β_k is ignored and $\gamma_k = 1$ if β_k should be considered as an effective variable.

$$\boldsymbol{\gamma} = (\gamma_1, \ldots, \gamma_K) \qquad \text{Eq. (2.13)}$$

The marginal posterior distribution of $\boldsymbol{\gamma}$, written as $\pi(\boldsymbol{\gamma} \mid Y)$, contains information about the variable selection. Based on observation Y, the posterior probability $\pi(\boldsymbol{\gamma} \mid Y)$ updates 2^K from the prior probabilities of possible

combinations of $\boldsymbol{\gamma}$ to find an apt subset of whole explanatory variables.

For the regression setup, involving all of the candidates of explanatory variables. The canonical regression set up is Eq. (2.14)

$$\begin{aligned} &Y \mid \beta, \sigma^2 \sim N\left(\mathbf{X}\beta, \sigma^2 I\right) \\ &\mathbf{X} = \left[X_1, \ldots, X_K\right] \\ &\beta = \left(\beta_1, \ldots, \beta_K\right)' \end{aligned} \qquad \text{Eq. (2.14)}$$

Among $\mathbf{X}$, some subset of variables affects Y , and the other variables have no relevance with Y. To extract information relevant to Y, consider Eq. (2.13) as a part of the hierarchical model. Then, assuming that β is a mixture of two normal distributions with different variances, the prior distribution of β_k is presented in Eq. (2.14).

$$\beta_k \mid \gamma_k \sim \gamma_k N\left(0,\ \tau_k^2\right) + \left(1-\gamma_k\right) N\left(0,\ \mathrm{c}_k^2 \tau_k^2\right) \qquad \text{Eq. (2.15)}$$

In Eq. (2.15), c_k^2 is assumed as some small constant, τ_k^2 is assumed to be large enough for appropriately estimating coefficients, and γ_k is a binary latent coefficient that takes only zero or one for its value. Introducing the latent binary variable γ_k facilitates the variable selection problem. When $\gamma_k = 1$,

$\beta_k \sim N\left(0,\ \tau_k^2\right)$, which implies that β_k is drawn from a normal distribution on a straight lane. When $\gamma_k = 0$, $\beta_k \sim N\left(0,\ c_k^2\tau_k^2\right)$, which implies that β_k is drawn from a small variance of sharp normal distribution. If β_k is drawn from $N\left(0,\ c_k^2\tau_k^2\right)$, then β_k is concentrated around zero, which consequently has the effect of removing the variable. The difference between the Spike-and-Slap mixture and the SSVS model is that Spike-and-Slap mixture assumes probability mass on $\beta_k = 0$ when $\gamma_k = 0$. But when implementing Gibbs sampler, if spike becomes point mass, then β_k generates reducible chains, which incurs nonconvergent chains and β_k is stuck to zero. (George & Mcculloch, 1997)

In multivariate form, Eq. (2.15) can be expressed as Eq. (2.16).

$$\begin{aligned} &\boldsymbol{\beta} \mid \boldsymbol{\gamma} \sim MVN_K\left(0, D_\gamma R D_\gamma\right) \\ &D_\gamma = diag\left(f\left(\boldsymbol{\gamma}\right)\right) \\ &f\left(\gamma_k\right) = \begin{cases} 1 & \text{if } \gamma_k = 1 \\ c_k^2 & o/w \end{cases} \end{aligned} \qquad \text{Eq. (2.16)}$$

In summary with parsimonious representation, the proposition of Gibbs sampler implementation of George and McCulloch (1993) is summarized in Eq. (2.17)

$$
\begin{aligned}
&Y \mid \beta, \sigma^2 \sim N\left(\mathbf{X}\beta, \sigma^2 I\right) \\
&\sigma^2 \sim IG\left(\kappa, \kappa\Psi\right) \\
&\beta \sim N\left(0, D_\gamma I D_\gamma\right) \\
&D_\gamma = diag\left(\boldsymbol{\gamma}\right) \\
&\boldsymbol{\gamma} = \left(\gamma_1, \ldots, \gamma_K\right) \\
&\gamma_k = \begin{cases} c & \text{if k-th element is excluded (some small c)} \\ 1 & \text{if k-th element is selected} \end{cases} \\
&\gamma_k \sim Bernoulli\left(p_k\right)
\end{aligned}
\qquad \text{Eq. (2.17)}
$$

George and McCulloch (1997) noted that the above formation of SSVS is non-conjugate prior since equation (2.16) does not depend on the residual variance σ since the variance of the beta is not adjustable. Let the estimated (selected) coefficients' variance be v_1, and the abandoned (non-selected) coefficients' variance v_0, assume that the intersection of estimated and abandoned distributions is δ. The relationship between v and δ is $\log\left(v_1 / v_0\right) \big/ \left(v_0^{-1} - v_1^{-1}\right) = \delta^2$. For sound estimation (proper classifying the estimated or the abandoned coefficients), the absolute value of the estimated coefficients exceeds the intersection of estimated and abandoned distribution, satisfying $|\beta| > \delta$. However, the significant difference between v_1 and v_0 also occurred computation problems. Therefore, through their experimental settings, the authors suggested that careful selection is needed for selecting the small parameter c, and it is apt to choose $v_1 / v_0 = 1/c^2 \leq 10000$. This dissertation chooses c as 0.01, following from Gilbride et

al. (2006).

2.3 Decision Heuristics and Alternative Decision Rules

In most cases, stated choice studies assume that respondents typically choose the most preferred alternatives among a listed hypothetical or realistic choice set that are designed by researchers and that respondents are expected to compare trade-offs between all attributes that consist of alternatives before choosing the most preferred alternative in a choice set. This assumption is based on an axiom that human beings are rational decision makers. Therefore, simplified random utility maximization (RUM) or linear additive utility is used extensively. However, respondents' choice behavior is a complex heterogeneous information process, and it is not desirable to express it in a RUM structure. In some cases, previous literature concluded that alternative decision rules, which embedd psychological structures, have more explanatory power compared to RUM structure (C. G. Chorus, Arentze, & Timmermans, 2008; Hess, Stathopoulos, & Daly, 2012). On the contrary, some literature reported that model fit of alternative decision rules worsens model fits (Hess et al., 2014) This section overviews decision heuristics and various alternative decision rules suggested in previous literature and exploits details of attribute non-attendance and random regret models.

2.3.1 Decision Heuristics in a Choice Model

The history of alternative decision rules in choice models is not quite long. The main topic of the discrete choice model has focused on elaborating models for consumer heterogeneity and deriving models to assume realistic errors that imply realistic correlation structures and substitution patterns (C. G. Chorus, 2014a). Those models assume that respondents decide with a weighted summation of attributes in alternatives, which has the form of Eq. (2.18), and assume the alternative with the highest utility among a choice set is chosen by respondents.

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} = \mathbf{X\beta} + \varepsilon_{ijt} \qquad \text{Eq. (2.18)}$$

Irrational decision-making behaviors were firstly suggested by Simon (1955), which suggested the concepts of bounded rationality of human beings, and was widely known by Tversky and Kahneman (1974), breakthrough research of heuristics. Heuristics have occurred in the decision-making process, where a decision cannot be made reasonably due to insufficient time or information, or a decision can be made by decision-makers, where systematic and rational judgment is not necessary.

Recently, alternative decision rules have been attracting attention of choice

modelers. Alternative decision rules mainly modify deterministic part of the utility V_{ijt} in Eq. (2.18) into structures that reflect psychological interpretation of decision-making behaviors of human beings. Such models are tabulated as follows.

Table 1. Alternative Decision Rules in Choice Modelling (Chorus, 2014)

Decision rule	Mathematical Formulation of decision rule
Elimination-by-aspects (Amos Tversky, 1972)	$y_i = 1 \Leftrightarrow$ $x_{im} \geq \tilde{x}_m, \ ^{\forall} m$ $\tilde{x}_m$: aspiration level for m-th attribute
Lexicographic (Hess et al., 2012)	$y_i = 1 \Leftrightarrow$ $x_{im} = \max_{\forall j \in C} \left[x_{jm} \right]$
Reference Dependent (I)	$y_i = 1 \Leftrightarrow V_i \geq V_j, \ ^{\forall} j \in C$ $V_i = \sum_m \begin{pmatrix} -\overleftarrow{\beta}_m \max\left[0, \bar{x}_m - x_{im}\right] \\ + \overrightarrow{\beta}_m \max\left[0, x_{im} - \bar{x}_m\right] \end{pmatrix}$ $\bar{x}_m$: reference of m-th attribute
Reference Dependent (II)	$y_i = 1 \Leftrightarrow V_i \geq V_j, \ ^{\forall} j \in C$ $V_i = \sum_m \begin{pmatrix} -\overleftarrow{\gamma}_m \max\left[0, \bar{x}_m - x_{im}\right]^{\varphi^m} \\ + \max\left[0, x_{im} - \bar{x}_m\right]^{\vartheta^m} \end{pmatrix}$ $\bar{x}_m$: reference point of m-th attribute

Relative Advantage (I) (Asymmetric)	$y_i = 1 \Leftrightarrow V_i \geq V_j,\ ^{\forall} j \in C$ $V_i = \sum_m \beta_m x_{im} + \delta \sum_{j \neq i} \frac{\sum_m A_m}{\sum_m A_m + \sum_m \left(B_m + \gamma_m \left\{ B_m \right\}^{\varphi^m} \right)}$ $A_m = \max\left[0,\ \beta_m \left(x_{im} - x_{jm} \right) \right]$ $B_m = \max\left[0,\ \beta_m \left(x_{im} - x_{jm} \right) \right]$
Relative Advantage (II) (Symmetric)	$y_i = 1 \Leftrightarrow V_i \geq V_j,\ ^{\forall} j \in C$ $V_i = \sum_m \beta_m x_{im} + \sum_{j \neq i} \frac{\sum_m A_m}{\sum_m A_m + \sum_m B_m}$ $A_m = \log\left[1 + \exp\left\{ \beta_m \left(x_{im} - x_{jm} \right) \right\} \right]$ $B_m = \log\left[1 + \exp\left\{ \beta_m \left(x_{jm} - x_{im} \right) \right\} \right]$
Contextual Concavity	$y_i = 1 \Leftrightarrow V_i \geq V_j,\ ^{\forall} j \in C$ $V_i = \sum_m \left(\beta_m \left\{ x_{im} - \min_{j \in C} \left[x_{jm} \right] \right\} \right)^{\varphi^m}$
Random Regret (I) (C. G. Chorus et al., 2008)	$y_i = 1 \Leftrightarrow R_i \leq R_j,\ ^{\forall} j \in C$ $R_i = \max_{j \neq i} \left(\sum_m \max\left[0,\ \beta_m \left(x_{jm} - x_{im} \right) \right] \right)$
Random Regret (II) (C. G. Chorus, 2010)	$y_i = 1 \Leftrightarrow R_i \leq R_j,\ ^{\forall} j \in C$ $R_i = \sum_m \sum_{j \neq i} \log\left[1 + \exp\left\{ \beta_m \left(x_{jm} - x_{im} \right) \right\} \right]$

Elimination-by-aspects (EBA) is inspired by cognitive effort minimization (Amos Tversky, 1972). EBA rule eliminates alternatives that have attributes below

par (continuous attributes) or do not have attributes (in dummy case) until one alternative is left. Lexicographic rule (Hess et al., 2012) is a rule that decision-maker focuses only on the most important attribute and chooses an alternative that has maximum value on the most important attribute. Those rules are based on the decision-makers to reduce information process efforts.

The rest of decision rules are based on contextual dependency: reference-dependent, relative advantage, contextual concavity, and random regret. Reference-dependent model is based on the prospect theory of Kahneman and Tversky (1979), with asymmetric reaction tendency toward loss domain and gain domain. Reference-dependent model assumes asymmetric reaction coefficients between gain domain and loss domain (Hess et al., 2012) (De Borger & Fosgerau, 2008; Stathopoulos & Hess, 2012). The gain domain is the superior domain to the current status of decision-maker (A_m), and loss domain is the inferior domain to the current status of decision-maker (B_m). The application for reference-dependent model usually measures asymmetric reaction toward positive area (gain domain) and negative area (loss domain), and such behavior is revealed well in consumer high-tech adoption behavior (Junghun Kim, Lee, & Ahn, 2016; Junghun Kim, Park, & Lee, 2018). In addition, reference-dependent models allow inconsistent sensitivity between gain/loss domain to attach concavity-convexity coefficients (Stathopoulos & Hess, 2012). Relative advantage model assumes that

decision makers consider both linear additive of the alternative and relative advantages of the alternative compared to suggested alternatives, which means that suggested alternatives serve as reference points of the focused alternative (Amos Tversky & Simonson, 1993). The relative advantage model has two forms, non-symmetric and symmetric formation. Asymmetric formation captures asymmetry between advantage and disadvantage of loss aversion coefficient and convexity coefficient (Leong & Hensher, 2014). The contextual concavity model takes a reference point as the least value of attributes in the choice set (Kivetz, Netzer, & Srinivasan, 2004). The coefficient of convexity/concavity is measured by power function coefficients, allowing the exponential form of diminishing marginal utility from baseline (C. G. Chorus & Bierlaire, 2013; Leong & Hensher, 2012). Random regret model (RRM) is the model that measures regret level by the difference between attribute values in alternatives that decision-maker did not choose and attribute values in the alternative chosen by decision-maker (Loomes & Sugden, 1982). If the regret level is lower than zero, which means that the chosen alternative has better values in attributes, regret diminishes to zero. The random regret model will be covered in detail at section 2.3.3.

Considering the above alternative decision-making structure, Hess et al., (2012) used the latent class structure to incorporate the coexistence of various actual behavioral process into a model. The combination of the classes included in Hess et al., (2012) formed as follows: RUM-lexicography, classes with different

reference points, RUM-EBA, and RUM-RRM. Hess et al., (2012) suggested that allowing heterogeneity in the behavioral process significantly improves model fit compare to RUM-only model.

2.3.2 Attribute Processing Behavior

Attribute processing behavior has long been of interest. Attribute processing behavior typically includes a multi-stage model of attribute processing, and attribute non-attendance (Moon, 2017). The usual approach for attribute processing behavior is to find the latent choice set for respondents and to find out respondents' latent choice set formation in the perspective of alternative reduction and attribute reduction. Due to the complexity of alternative-attribute matrix formation, respondents made a decision by reducing the dimension of alternative or the dimension of attributes suggested in a choice situation.

The focus of this section is attribute non-attendance (ANA) behavior of respondents. Assumption of rational human behavior has long been challenged (Simon, 1955), because there is no guarantee that respondents consider all the attributes suggested in the choice sets in a multi attribute choice situation. Hensher (2006) implied that the complexity of the stated choice experiments is determined by design dimensionality, designs with large number of attributes and alternatives. In other words, respondents have utility for only a few of the

attributes associated with their concerns or respondents cannot attend to all attributes in a choice set due to its complexity and their cognitive constraints. Moreover, in an attribute-alternative matrix with a different formation, respondents were induced different preference. In counterpart, the different forms of the attribute-alternative matrix do not affect respondents' decision-making strategy (Sandorf, Crastes dit Sourd, & Mahieu, 2018), but the elicited preference differs. Therefore, finding the subset of attributes for consumer utility has been a critical issue.

Mainly, ANA model is studied in two streams, inferred ANA and stated ANA. Some researches include self-reported statements on the survey to ask which attributes respondents attended while making decision, which implies stated ANA (Carlsson, Kataria, & Lampi, 2010; Hensher, 2006; Hensher & Rose, 2009; Islam, Louviere, & Burke, 2007), while other researches cover inferred ANA behavior with suitable statistical modeling based on data (Gilbride et al., 2006; Rigby & Burton, 2006; Riccardo Scarpa, Gilbride, Campbell, & Hensher, 2009), or incorporating both inferred and stated ANA (R. Scarpa et al., 2013). In addition to observing the behavior in decision making process, recent studies use eye-tracking device to track respondents' attendance toward a choice situation (Shi, Wedel, & Pieters, 2013).

The usual approach for inferred ANA is a latent class model and a mixture of normal distribution with one centered sharply at zero. Scarpa et al. (2009)

compare both models of inferred ANA, and they suggested that both models show consistent results toward explaining inferred ANA.

The typical caveat aroused in stated ANA is that the statements from respondents may inaccurately be collected due to respondents' bias and misperception. However, Scarpa et al. (2013) proved that the stated ANA is quite useful and informative in the data set they used.

2.3.3 Random Regret Model

The random regret model formation is inspired by the regret theory (Bell, 1982; Fishburn, 1982; Loomes & Sugden, 1982) that provides evidence of risk avoidance behavior when choosing among risky alternatives (C. G. Chorus, 2010; C. G. Chorus et al., 2008). Regret theory assumes that the preference structure of decision makers is derived from the comparison between the alternative that the decision-maker has chosen and the other considered alternatives, which are the non-chosen alternatives. If the performance of non-chosen alternatives is better than the chosen one, then the decision-makers' regret would arise, or rejoice would occurred otherwise. Therefore, the modified deterministic utility function of decision-maker *i* consists of conventional deterministic utility and regret from other alternatives (Eq. 2.19).

$$MV_{ij} = V_{ij} + R_{ij} = V_i + f\left(V_{ij} - V_{im}\right) \qquad \text{Eq. (2.19)}$$

Quiggin (1994) extended regret theory to the general situation (multiple alternatives situation) and suggested that the regret of chosen alternative is derived from the best-foregone alternative, which refers to principle of Irrelevance of Statewise Dominated Alternatives (ISDA, Eq. (2.20)). This form of regret removes the notion of the rejoice, that has symmetrical and compensatory nature of utility. Subsequent papers about regret models in choice modeling do not consider the rejoice in regret models. Therefore, random regrets in the choice model have a characteristic of semi-compensatory rules.

$$R_{ij} = \max_{m \neq j} R_{ijm} = \max_{m \neq j} f\left(V_{ij} - V_{im}\right) \qquad \text{Eq. (2.20)}$$

Chorus et al., (2008), renowned paper of RRM, suggests the concept of regret in discrete choice models by assuming that decision-makers minimize their regrets while making judgment to minimize maximized regret, which is referred to as RRmax (Rasouli & Timmermans, 2014) Following Quiggin's (1994) ISDA concepts, the specification of regret of Chorus et al., (2008) is shown in Eq. (2.21), individual *i*'s regret with selecting alternative *j* compare to other alternatives m, from linear level (continuous) attribute *k*. Eq. (2.21) captures

negative emotion from attribute *k* selecting alternative *j*, which captures semi-compensatory behavior of decision-maker *i*. This formation is similar to rectified linear unit (ReLU) concepts, where negative values of regret (rejoice) become zero, and only positive value of regret is activated. (Figure. 3)

$$R_{ijmk} = \max\left[0, \beta_k \left(x_{imk} - x_{ijk}\right)\right], \qquad \text{Eq. (2.21)}$$

The total regret of individual *i* selecting alternative *j* compared to alternative *m* is shown in Eq. (2.22). To satisfy ISDA restriction, the regret of individual *i* from chosen alternative *j* is the maximum value of regret among the regret derived from non-chosen alternatives *m*, shown in Eq. (2.23).

$$R_{ijm} = \sum_k \max\left[0, \beta_k \left(x_{imk} - x_{ijk}\right)\right] \qquad \text{Eq. (2.22)}$$

$$R_{ij} = \max_{m \neq j} \left\{ \sum_k \max\left[0, \beta_k \left(x_{imk} - x_{ijk}\right)\right] \right\} \qquad \text{Eq. (2.23)}$$

The discrete choice formation is similar to the multinomial logit model, except for the replacement of deterministic part of regret R_{ij}. ε_{ij} follows i.i.d., Gumbel distribution (Eq. (2.24)). Therefore, the choice probability of individual *i* choosing alternative *j* is shown in Eq. (2.25), which represents the choice toward minimized

maximum regrets from choosing alternative *j*.

$$RR_{ij} = -R_{ij} + \varepsilon_{ij} \qquad \text{Eq. (2.24)}$$

$$P_{ij} = \frac{\exp\left(-R_{ij}\right)}{\sum_{m} \exp\left(-R_{im}\right)} \qquad \text{Eq. (2.25)}$$

However, the systematic regret form suggested by Chorus et al., (2008) has two limitations. First, the form only regards the best of foregone alternatives, which constrained ISDA assumption, whereas consumer intuitively feels the regret from the presence of all the other foregone alternatives that perform better than the chosen one. Second, the form of Eq. (2.23) have nondifferentiable forms, which creates difficulties in estimation and deriving marginal effects of alternatives and elasticities. (C. G. Chorus, 2010)

Therefore, following from Chorus et al., (2008), Chorus (2010) proposed an alternative specification of RRM, removing ISDA restriction from Chorus et al., (2008) and transforming regret as differentiable form. The systematic regret model suggested in Chorus (2010) is shown in Eq. (2.27), which is called RRSum (Rasouli & Timmermans, 2014) or PureRRM (van Cranenburgh, Guevara, & Chorus, 2015).

Assuming that a decision-maker *i* faces a set of *J* alternatives with *K* attributes,

a decision-maker *i* compare alternatives among a set of alternatives. For a decision-maker *i* comparing alternative *j* and *m*, and considering alternative *j*, the pairwise regret from attribute k, is shown in Eq. (2.26), which is a soft plus functional form.

$$R_{j\leftrightarrow m} = \log\left(1+\exp[\beta_k\left(x_{mk}-x_{jk}\right)\right) \qquad \text{Eq. (2.26)}$$

The main difference between regret forms of Chorus et al., (2008) [Eq. (2.22)] and Chorus (2010) [Eq. (2.26)] is the smoothness of the functional form (Figure. 3). The caveat of each form is that RRmax is nondifferentiable form and RRsum has no zero values on reference points.

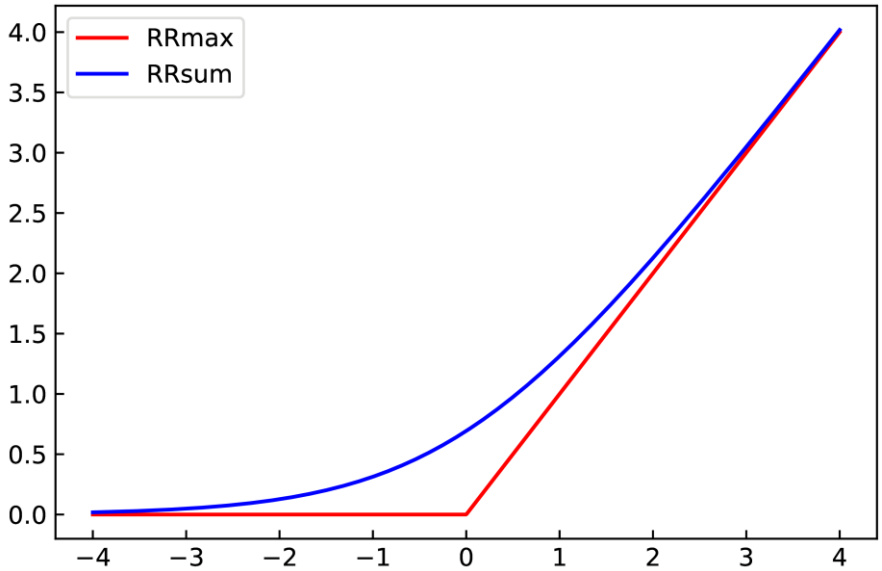


Figure 3. Functional Form of RRmax and RRsum

Systematic regret R_{ij}, from comparing all the alternatives in a choice set, is shown in Eq. (2.27), therefore, the choice probability of alternative *j* is described in Eq. (2.28).

$$R_{ij} = \sum_{j \neq m} \sum_{k} \log\left[1 + \exp\left\{\beta_m \left(x_{mk} - x_{jk}\right)\right\}\right] \qquad \text{Eq. (2.27)}$$

$$P_{ij} = \frac{\exp\left(-R_j\right)}{\sum_m \exp\left(-R_m\right)} \qquad \text{Eq. (2.28)}$$

Chorus (2014b) suggests subtracting $\log(2)$ from pairwise logarithm in the RRM model. At the reference point, in which $X_{mk} = X_{jk}$, the representation of regret shows nonnegative in RRsum logarithm specification. Therefore, by subtracting $\log(2)$ [Eq. (2.29)], the regret approaches to zero when the chosen alternative has the same values in the attribute. However, this specification did not change choice probability and therefore removed rejoice from regret. (Rasouli & Timmermans, 2018)

$$R'_{ij} = \sum_{m \neq j} \sum_{k} \left[\log\left\{ 1 + \exp\left(\beta_k \left(X_{imk} - X_{ijk} \right) \right) \right\} - \log(2) \right] \qquad \text{Eq. (2.29)}$$

The specification of regret may show different results context by context. In some decision contexts, the RRmax, based on ISDA principle, showed better performance, whereas in another context, RRsum showed better performance. Hensher et al., (2015) persisted that the model fit issue may have occurred based on the choice set contexts. If someone recognizes the dominant alternative in the choice set, relatively, then respondent feels regret from the dominant alternative, and the difference between the alternatives is easily recognized by respondents. In other cases, if all the alternatives are shown to be competitive in the view of the respondents', then the respondent feels regret while comparing the alternatives.

In the context of comparing RRM (especially RRsum) with RUM, the main differences between RUM and RRsum models are summarized as follows: IIA property, parameter interpretation, and semi-compensatory behavior of RRM. RRM does not exhibit the IIA property since the decision structure is made choice set specific and affected by other alternatives. [Eq. (2.30)]

$$\frac{P_j}{P_l} = \frac{\exp\left(-R_j\right) \Big/ \sum_m \exp\left(-R_m\right)}{\exp\left(-R_l\right) \Big/ \sum_m \exp\left(-R_m\right)} = \frac{\exp\left(-R_j\right)}{\exp\left(-R_l\right)}$$
$$= \frac{\exp\left(-\sum_{j \neq m} \sum_k \log\left[1 + \exp\left\{\beta_m \left(x_{mk} - x_{jk}\right)\right\}\right]\right)}{\exp\left(-\sum_{l \neq m} \sum_k \log\left[1 + \exp\left\{\beta_m \left(x_{mk} - x_{jk}\right)\right\}\right]\right)} \qquad \text{Eq. (2.30)}$$

Hensher Greene and Chorus (2013) independently applied RUM and RRM models into durable goods, vehicles with different fuel type choice behavior, and compared RUM and RRM in the context of strategic choices. They believed that the minimization of anticipated regret is an important factor when the choice circumstances are believed to be difficult and important, which is suitable for a durable good. Therefore, they suggested that the parameter estimated in RRM and RUM should also be interpreted in different ways. The RUM parameters imply the contribution of an attribute to the respondents' utility of choosing an alternative, whereas the RRM parameters imply the contribution of potential

regret associated with an alternative. In conclusion, direct comparison between parameters in RUM and those of RRM might be useless. Therefore, the direct choice elasticities, which denotes the percent change in the probability occurred when 1% change in the level of the attribute value, are comparable between RUM and RRM model (Hensher et al., 2013). The decision-making structure of RRM depends on the choice context, and the elasticities of RUM and RRM are each shown in Eq. (2.31), and Eq. (2.32).

$$E_{RUMx_{ij}} = \frac{\partial P_{ij}}{\partial x_{ij}} \frac{z_{ij}}{P_{ij}} = \frac{\partial V_{ij}}{\partial x_{ij}} z_{ij} \left(1 - P_{ij}\right) \qquad \text{Eq. (2.31)}$$

$$E_{RRMx_{lm}} = \frac{\partial \ln P_j}{\partial x_{lm}} = \sum_m \left(P_j \frac{\partial R_m}{\partial x_{lm}} \right) - \frac{\partial R_j}{\partial x_{lm}} \qquad \text{Eq. (2.32)}$$

As regret is derived from the difference in attribute values between alternatives, RRM shows semi-compensatory or compromise behavior, contrast to RUM has fully-compensatory behavior (C. Chorus, 2012).

There is another stream of literature in RUM and RRM, within-sample heterogeneity. Hess et al. (2012) provided clear evidence of within-sample heterogeneous structure. Then, Hess and Stathopoulus (2013), used a latent class model and latent character traits to discern consumer heterogeneous decision-

making structure. Also, they allowed within-class heterogeneity by using two-stage latent class approaches. While specifying decision groups, they adopt unobservable character traits as latent variables and divide RUM group and RRM group with the latent class model, which the class inclusion probability depends on latent traits.

Chorus, Rose & Hensher (2013), which the concept is similar to this dissertation, suggested that the structure of the decision-maker depends on its attributes, meaning that the structure of the deterministic part of the utility is consistent with a mixture of utility and regret, called hybrid utility. The random modified utility (RMU) or the hybrid RUM-RRM from choosing alternative *i* is described in Eq. (2.33)

$$\begin{aligned} RMU_i &= MU_i + \varepsilon_i = \sum_{m=1\ldots q} UM_{im} + \sum_{m=q+1,\ldots,M} RM_{im} \\ &= \sum_{m=1\ldots q} \beta_m x_{im} + \sum_{m=q+1,\ldots M} \sum_{j \neq i} -\log\left\{1+\exp\left[\beta_m\left(x_{jm}-x_{im}\right)\right]\right\} + \varepsilon_i \end{aligned} \quad \text{Eq. (2.33)}$$

Also, they suggested marginal willingness-to-pay (WTP) measures in this hybrid model, directly in the comparison between random regret components and random utility components (C. Chorus, 2012; C. G. Chorus et al., 2013).

Assuming that *r*-th attribute is the cost attribute, which can be RUM and RRM, and *t*-th attribute represents an attribute excepts for the cost attribute, also RUM

and RRM, the combination of four WTP is derived in Eq. (2.34)

$$
\begin{aligned}
WTP_{RUM}^{RUM} &= -\frac{\partial MU_i}{\partial x_{it}} \Big/ \frac{\partial MU_i}{\partial x_{ir}} = -\frac{\beta_t}{\beta_r} \\
WTP_{RUM}^{RRM} &= \left(\sum_{j \neq i} \left[-\beta_t \Big/ \left(1 + 1 \Big/ \exp\left[\beta_t \left(x_{jt} - x_{it} \right) \right] \right) \right] \right) \Big/ \beta_r \\
WTP_{RRM}^{RUM} &= \beta_t \Big/ \left(\sum_{j \neq i} \left[-\beta_r \Big/ \left(1 + 1 \Big/ \exp\left[\beta_r \left(x_{jr} - x_{ir} \right) \right] \right) \right] \right) \\
WTP_{RRM}^{RRM} &= \frac{\left(\sum_{j \neq i} \left[-\beta_t \Big/ \left(1 + 1 \Big/ \exp\left[\beta_t \left(x_{jt} - x_{it} \right) \right] \right) \right] \right)}{\left(\sum_{j \neq i} \left[-\beta_r \Big/ \left(1 + 1 \Big/ \exp\left[\beta_r \left(x_{jr} - x_{ir} \right) \right] \right) \right] \right)}
\end{aligned}
\qquad \text{Eq. (2.34)}
$$

Chorus et al. (2013) noted that although the conventional WTP is defined in WTP_{RUM}^{RUM}, the existence of conventional WTP does not necessarily imply that below WTP equations exist. As RRM is the choice set specific estimation, WTP that includes RRM is the choice set specific and could be changed. However, they also noted that WTP measures in RRM are well suited in various datasets. Also, they suggested that allowing WTP concepts in a hybrid formation imply a more vibrant interpretation of the trade-offs between alternatives. The WTP of RRM takes a concave form, which suggests that the attribute increment in small amount entails a considerable reduction in regret and the reduction decay as attribute

difference become smaller.

After Chorus et al. (2013), several studies showed the validity of the hybrid RUM-RRM framework in several datasets (Dekker, Hess, Arentze, & Chorus, 2014; Jinhee Kim, Rasouli, & Timmermans, 2017; Wang, Monzon, Di Ciommo, & Kaplan, 2014). The prevailing opinion of these researches is that RRM and Hybrid specification of RUM-RRM outperform RUM in many cases in terms of model fit and predictive ability (C. Chorus, van Cranenburgh, & Dekker, 2014).

2.4 Limitations of Previous Research and Research Motivation

The current research has distinctive features when compared to previous studies in two critical folds. First, the previous heterogeneous variable selection methodology suggested by Gilbride et al., (2006) did not consider individual characteristics toward attribute non-attendance behavior. The randomized latent parameter simply explores which attributes are considered in respondents' choice situations. However, attribute non-attendance behavior is determined by the characteristics of respondents or choice situations and is heterogeneous across individuals. The HVS has only dealt with heterogeneity of respondents.

Also, the second drawback of the previous approaches was the encounterwith heterogeneous decision rule behaviors. It has been difficult to recognize heterogeneous decision rules individually. Although latent class approach was

used to deal with heterogeneity of decision rules, the latent class model is not well suited to capture the heterogeneity of individual decision structures.

Therefore, this study suggests a model that can overcome the above two limitations. The goal of this dissertation is identifying individual decision-making rule heterogeneity at a glance with respondents' traits. Chapter 3 will suggest new models that overcome such limitations.

Chapter 3. Model

This chapter proposes a new methodology to analyze consumer preference in decision-making strategy heterogeneity and consumer characteristics. Chapter 3.1 briefly overviews the overall framework of the new methodology. Next, Chapter 3.2 and Chapter 3.3 describes the proposed methodologies, a heterogeneous variable selection choice model with covariates and a heterogeneous choice model for respondent decision heuristic strategy in respective order.

3.1 Methodological Framework

This section proposes the overall suggested methodological framework of this dissertation. The proposed methodology is in two folds: A heterogeneous variable selection model with respondent covariates and a heterogeneous choice model for respondent decision heuristic strategy. The methodology proposed in this dissertation can provide the capability of analyzing heterogeneous respondents' characteristics of variable selection and alternative decision heuristics. Figure. 4 and Figure. 5 each summarize the proposed modeling concepts.

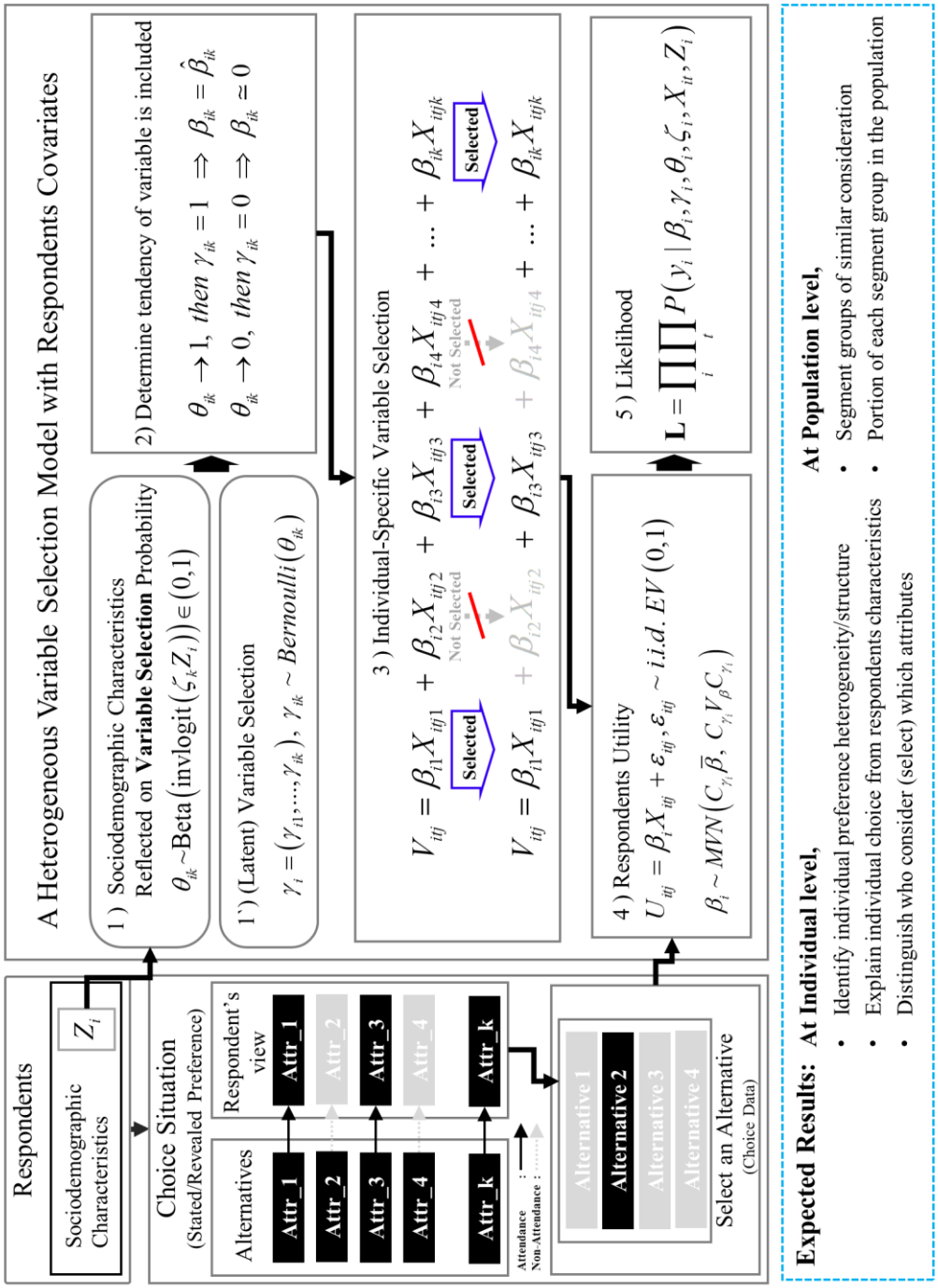


Figure 4. Schematic Illustration of the Proposed Model (I)

Conceptually, individual-specific variable selection probabilities are affected by individual characteristics (Z_i) in model 1 (A Heterogeneous Variable Selection Choice Model with Respondent Covariates). When the individual characteristic determines the variable selection probability, it is determined whether or not the specific variable is included in the model (γ_i). Afterward, individual utility coefficients (β_i) are extracted from within-sample averages $(\bar{\beta})$ to determine the individual utility of respondents.

The main difference between the HB multinomial logit with individual covariates and the suggested model is that the suggested model not only reduces individual utility parameters close to zero but also influences variance structure, which eliminates the bias of estimation while eliminating unnecessary covariance structures. Attribute presence and absence impacted both mean of utility and choice variability significantly (Islam et al., 2007). Therefore, for an individual level, eliminating covariance structures consequently reduces the bias of individual utility. In the whole sample level, eliminating individual-specific covariance structures consequently reduces the bias may occur while estimating the elements of variance-covariance.

The proposed model excels in estimating respondents' ANA behavior without any additional complicated information. Although previous studies have shown that ANA behaviors may be different depending on the characteristics of

respondents, previous research does not reflect the characteristics of respondents, only depends on stochastic or semi-parametrized searching attendance behavior. Also, the model for tracking ANA behavior by recording the respondent's eye-tracking motion behavior through a sophisticated device is hard to obtain. Although this direct observation of respondents' ANA behavior is more delicate and accurate, it is hard to apply in the conventional conjoint survey. Also, directly tracking the ANA of the respondent only reflects on the final choice set formation manually, which cannot guarantee better performance. This model has the advantage in that it can estimate more precisely than the existing method because it estimates the A-NA behavior through the characteristics of the respondents and the response pattern of the respondents.

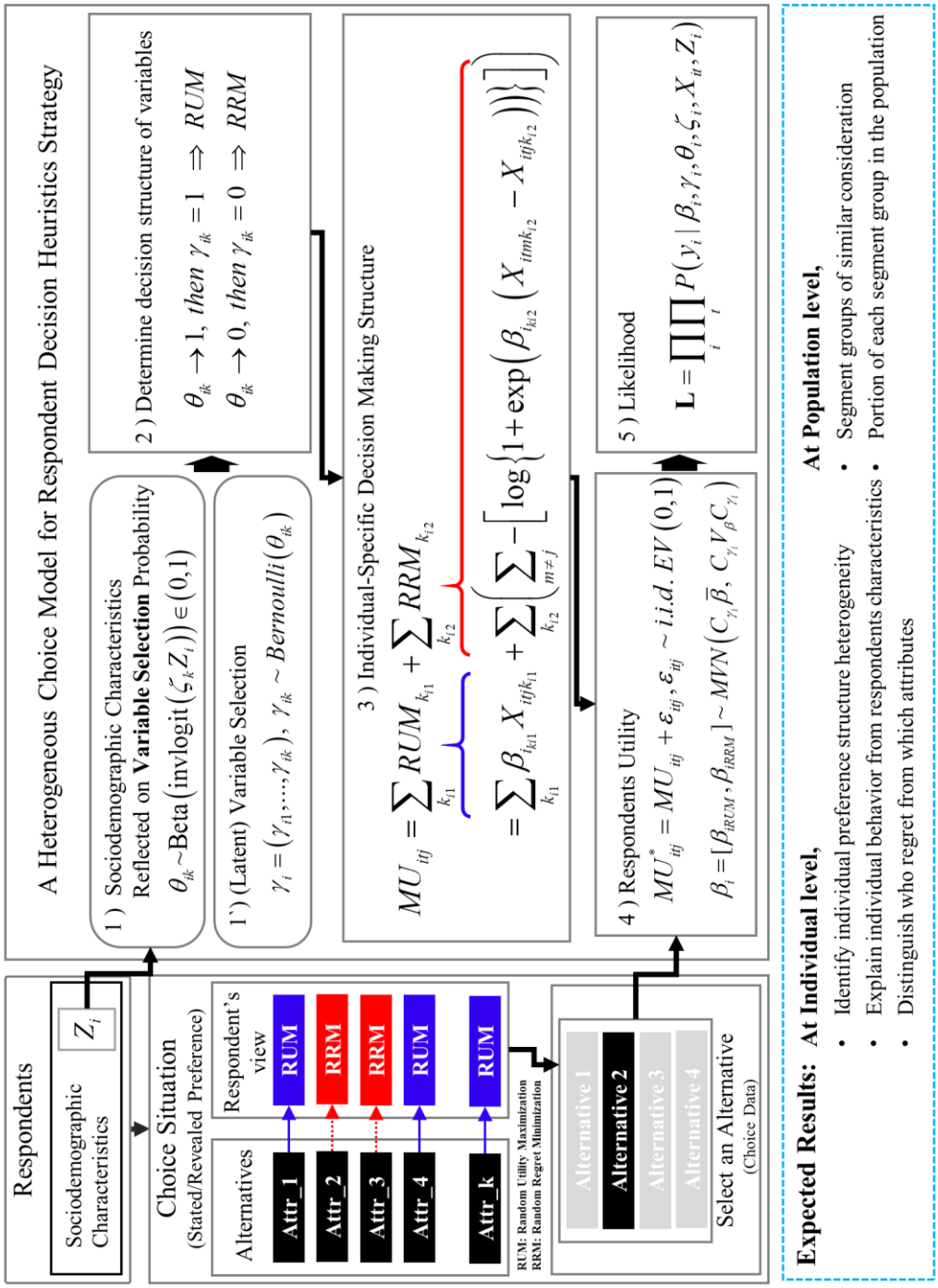


Figure 5. Schematic Illustration of the Proposed Model (II)

3.2 Heterogeneous Variable Selection Choice Model with Respondent Covariates

This section describes a heterogeneous SSVS choice model with respondent covariates. The utility that respondent *i* obtains from choosing alternative *j* in situation *t* is expressed as Eq. (3.1), where ε_{itj} is i.i.d. Gumbel distribution.

$$U_{itj} = V_{itj} + \varepsilon_{itj} = \boldsymbol{\beta}_i \mathbf{X}_{itj} + \varepsilon_{itj} = \sum_k \beta_{ik} X_{itjk} + \varepsilon_{itj} \qquad \text{Eq. (3.1)}$$

To incorporate heterogeneity into the stochastic search variable selection suggested by George and McCulloch (1993, 1997), Gilbride et al., (2006) suggests a method to specify heterogeneity variable selection (HVS). This proposal extends the HVS model to incorporate respondents' characteristics. Individual specific utility coefficients are drawn from multivariate normal distribution in Eq. (3.2).

$$\begin{aligned} &\beta_i \sim MVN\left(C_{\tau i}\bar{\beta},\ C_{\tau i} V_\beta C_{\tau i}\right) \\ &C_{\tau i} = diag\left(\tau_{i1}, \tau_{i2}, ..., \tau_{iK}\right) \end{aligned} \qquad \text{Eq. (3.2)}$$

In Eq. (3.2), $C_{\tau i} = diag\left(\tau_{i1}, \tau_{i2}, ..., \tau_{iK}\right)$ is individual-specific variable selection latent parameter of utility coefficients that permits which variables are used by

individual *i*. V_β is a variance-covariance matrix of utility coefficient. To efficiently draw individual-specific utility coefficient, this dissertation utilizes affine transformation of i.i.d. normal distribution, as shown in Eq. (3.3)

$$\begin{aligned} &\beta_i = C_{\tau i}\bar{\beta} + C_{\tau i}V_\beta^{1/2}\tilde{\beta}_i \\ &\tilde{\beta}_i \sim MVN\left(\mathbf{0}, I_K\right) = N\left(0,1\right)\cdot N\left(0,1\right)\cdot\ldots\cdot N\left(0,1\right) \\ &\bar{\beta} = \left(\bar{\beta}_1, \bar{\beta}_2, \ldots, \bar{\beta}_K\right) \end{aligned} \qquad \text{Eq. (3.3)}$$

The $V_\beta^{1/2}$ is a lower diagonal Cholesky decomposition of variance-covariance matrix, i.e., square root of the variance-covariance matrix $V_\beta = \left(V_\beta^{1/2}\right)\left(V_\beta^{1/2}\right)^T$. $V_\beta^{1/2}$ is drawn from LKJ correlation distribution with half-Cauchy distributed standard deviation (Lewandowski, Kurowicka, & Joe, 2009). k refers to the dimension of the matrix, η refers to the shape parameter of LKJ distribution, which implies a uniform distribution of the correlation matrices when $\eta = 1$, and an identity matrix when η has larger value. ϖ is a standard distribution parameter included in the half-Cauchy distribution, and larger ϖ implies flattened thick-tailed distribution.

$$V_\beta^{1/2} \sim LKJCov\left(k, \eta, \varpi\right) \qquad \text{Eq. (3.4)}$$

The betabar $\bar{\beta}$, pooled parameter of utility coefficient is drawn from a multivariate normal distribution with zero mean vector and identity variance-covariance matrix [Eq. (3.5)]. Previous literature (Gilbride et al., 2006) uses more flattened prior for betabar distribution. However, as it shows consistent results in the suggested model, this dissertation used a standard multivariate normal distribution for betabar.

$$\bar{\beta} \sim MVN(0, I) = N(0,1) \cdot N(0,1) \cdot \ldots \cdot N(0,1) \qquad \text{Eq. (3.5)}$$

The diagonal component $\tau_{ik} \in \{c, 1\}$ has a value of c or 1, some small coefficient c which is small enough to reduce utility coefficient near zero and one which allows inferences on the variables countered in decision making. This dissertation uses $c = 0.01$, suggested from George and McCulloch (1993, 1997). τ_{ik} is drawn from Bernoulli distribution where the probability of one is θ_k, and the probability of c is $(1-\theta_k)$.

$$\tau_{ik} \sim Bernoulli(\theta_k) \qquad \text{Eq. (3.6)}$$

Gilbride et al., (2006) uses Beta distribution to draw θ_k [Eq. (3.7)]. However, the drawback of this hyper parametrization is that all respondents have the same

probability with that of selecting specific attributes. Therefore, this dissertation used latent parameters θ_{ik} that include respondents' characteristics in linear form. [Eq. (3.8)].

$$\theta_k \sim Beta(a,b) \qquad \text{Eq. (3.7)}$$

$$\begin{aligned} &\theta_{ik} \sim Beta(a,b) = Beta(\mu_{ik}, \phi_{ik}) \\ &\mu_{ik} = \frac{a}{a+b} = \text{logit}^{-1}(Z_i \cdot \zeta_k) \ or \ probit^{-1}(Z_i \cdot \zeta_k) \\ &\phi_{ik} = \frac{\sqrt{\mu_{ik}(1-\mu_{ik})}}{1+a+b} \end{aligned} \qquad \text{Eq. (3.8)}$$

The specification suggested in Eq. (3.8) assumes that individual variable selection is affected by individual characteristics. Individual *i*'s covariates, which usually are individual characteristics and sociodemographic characteristic, are noted as Z_i. Then the mean of variable selection parameter is either inverse logit or inverse probit of a linear combination of Z_i and variable selection coefficient ζ_k. Therefore, the coefficient ζ_k captures the sociodemographic impact on selecting variable *k*.

$$\zeta_k \sim MVN(z_k, \sigma_{z_k}) \qquad \text{Eq. (3.9)}$$

Then, the likelihood of choice probability $L(\beta \mid Y)$ is shown in Eq. (3.10)

$$L(\beta \mid Y) = \prod_i \prod_t P_{itj}\left(X_{it} \mid \boldsymbol{\beta}_i, \boldsymbol{\gamma}_i\right) = \prod_i \prod_t \frac{\exp\left(X_{itj}\boldsymbol{\beta}_i\right)}{\sum_m \exp\left(X_{itm}\boldsymbol{\beta}_i\right)} \qquad \text{Eq. (3.10)}$$

As the suggested model is in hierarchical Bayesian setting, the posterior distribution for the model is defined in Eq. (3.11).

$$\begin{aligned} &P\left(V_\beta, \bar{\beta}, \tau, \theta, \zeta \mid Y, X, Z\right) \propto \\ &\quad L(Y \mid \beta) P\left(\beta \mid \bar{\beta}, \tau, \theta, \zeta\right) P(\tau \mid \theta, \zeta) P(\theta \mid \zeta) P(\zeta) P\left(\bar{\beta}\right) P\left(V_\beta\right) \end{aligned} \qquad \text{Eq. (3.11)}$$

In this specification, as continuous distributions (Beta distributions, Normal distributions, and half-Cauchy distributions) are drawn from NUTS sampler, Bernoulli distribution from the variable selection is drawn separately from binary Gibbs Metropolis sampling algorithm. Therefore, the conjugate form of the posterior distribution of the proposed model is shown in Eq. (3.12), which takes a conjugate form since the posterior distribution is composed of a combination of exponential families.

$$
\begin{aligned}
&P\left(V_\beta, \bar{\beta}, \tau, \theta, \zeta \mid Y, X, Z\right) \propto \\
&\quad L\left(Y \mid \beta\right) P\left(\beta \mid \bar{\beta}, \tau, \theta, \zeta\right) P\left(\theta \mid \zeta\right) P\left(\zeta\right) P\left(\bar{\beta}\right) P\left(V_\beta\right) \\
&\propto \left[\prod_i \prod_t \frac{\exp\left(X_{itj}\boldsymbol{\beta}_i\right)}{\sum_m \exp\left(X_{itm}\boldsymbol{\beta}_i\right)}\right] \cdot \\
&\quad \left[\exp\left(-\frac{1}{2}\left(C_\tau\left(\boldsymbol{\beta}-\boldsymbol{\mu}_\beta\right)\right)'\left(C_\tau V_\beta C_\tau\right)\left(C_\tau\left(\boldsymbol{\beta}-\boldsymbol{\mu}_\beta\right)\right)\right)\right] \cdot \\
&\quad \left[\frac{\Gamma\left(a+b\right)}{\Gamma\left(a\right)\Gamma\left(b\right)}\theta^{a-1}\left(1-\theta\right)^{b-1}\right] \cdot \\
&\quad \left[\exp\left(-\frac{1}{2}\left(\zeta-\boldsymbol{\mu}_\zeta\right)' V_\zeta\left(\zeta-\boldsymbol{\mu}_\zeta\right)\right)\right] \cdot \\
&\quad \left[\exp\left(-\frac{1}{2}\left(\bar{\beta}-b\right)'\left(\bar{\beta}-b\right)\right)\right] \cdot \left[\prod_k L_{kk}^{K-k+2\eta-2}\right]
\end{aligned}
\qquad \text{Eq. (3.12)}
$$

3.3 Heterogeneous Choice Model for Respondent Decision Heuristics Strategy

In addition to the previously proposed model, Heterogeneous Variable Selection Choice Model with Respondent Covariates, this section extends the above model to identify decision heuristics: Heterogeneous Choice Model for Respondent Decision Heuristics Strategy (HDH RUM-RRM). Assuming that two forms of heterogeneous decision-making strategies being used among respondents: Random Utility Maximization (RUM) and Random Regret Minimization (RRM). Chorus (2010) hinted that linear additive structure and

regret models can be included in a modified deterministic utility. The inclusion of both decision-making strategies in the deterministic part of utility is of recent interest in the academia and has already been covered in several fields of literature (C. G. Chorus et al., 2013; Hensher et al., 2013). Especially, Chorus et al. (2013) suggests a hybrid RUM-RRM model, which posits attribute by attribute difference in the decision-making structure. As the referee of Chorus et al. (2013) pointed out that there is no evidence that the units of the regret part and the utility part in the hybrid decision-making structure are directly comparable, Chorus et al. (2013) suggested that the estimated relative weights of regret part did not significantly differ from one at any level of statistical significance. Therefore, it is concluded that the hybrid of RUM and RRM model is comparable in all cases. Also, empirical evidence in Chorus et al. (2013) suggested that a hybrid RUM-RRM structure performs better than RUM-only and RRM-only models in terms of log-likelihoods.

Assume that the attribute k_{RUM} is processed based on RUM structure $\left(k_{RUM} \in RUM\right)$ and the attribute k_{RRM} is processed RRM based decision-making structure $\left(k_{RRM} \in RRM\right)$. This means that the attributes in RUM are evaluated within utility maximization decision-making structure, and the attributes in RRM are evaluated within regret minimization decision-making structure. Then, the modified utility MU_{itj} containing RUM and RRM decision-making structure is

shown in Eq. (3.13).

$$
\begin{aligned}
MU_{itj} &= \sum_{k_{RUM} \in RUM} V_{k_{RUM}} + \sum_{k_{RRM} \in RRM} R_{k_{RRM}} \\
&= \sum_{k_{RUM} \in RUM} \beta_{ik_{RUM}} X_{itjk_{RUM}} \\
&\quad + \sum_{k_{RRM} \in RRM} \sum_{m \neq j} -\left[\log\left\{ 1 + \exp\left(\beta_{ik_{RRM}} \left(X_{itmk_{RRM}} - X_{itjk_{RRM}} \right) \right) \right\} \right]
\end{aligned}
\qquad \text{Eq. (3.13)}
$$

Here, the most critical problem is identifying which attributes follow RUM structure and which attributes follow RRM. In order to identify the structure, this dissertation uses the heterogeneous variable selection technique of the previously suggested methodology to isolate decision-making structure. For convenience, the equation is not presented in the order of attributes, but let RUM be the attribute shown first and RRM the attribute shown after. Here, note that the dummy attributes are not included in structure heterogeneity since there is no structural difference between RUM and RRM in dummy variable cases. Large a portion of the papers in RRM fields analyzed without dummy, and dummy variable in RRM is structurally similar to RUM (see Appendix. 4). Also, M.C. Dee (2016) quoted van Cranenburgh's phrase, that dummy variable has structural similarities in RUM and RRM formula. Therefore, continuous attributes are encountered in structure heterogeneity. Let the number of dummy attributes be k_d , and the number of continuous attributes k_c , then the modified utility coefficients for individual *i* can

be described as Eq. (3.14).

$$\begin{aligned}\beta_i &= \left(\beta_{iDUMMY}, \beta_{iRUM}, \beta_{iRRM}\right) \\ &= \left(\beta_{iDUMMY_1}, ..., \beta_{iDUMMY_{k_d}}, \beta_{iRUM_1}, ..., \beta_{iRUM_{k_c}}, \beta_{iRRM_1}, ..., \beta_{iRRM_{k_c}}\right)\end{aligned} \quad \text{Eq. (3.14)}$$

Before incorporating the structure from Eq. (3.2), dummy attributes cannot be encountered in structure heterogeneity. Therefore, the individual-specific structure selection latent parameter is described in Eq. (3.15).

$$\begin{aligned}C_{\tau i} &= diag\left(1_{iDUMMY}, \tau_{iRUM}, \tau_{iRRM}\right) \\ &= diag\left(1_1, ..., 1_{k_d}, \tau_{iRUM1}, ..., \tau_{iRUM_{k_c}}, \tau_{iRRM_1}, ..., , \tau_{iRRM_{k_c}}\right) \\ &= diag\left(1_1, ..., 1_{k_d}, \tau_{iRUM1}, ..., \tau_{iRUM_{k_c}}, \left(1-\tau_{iRUM1}\right), ..., , \left(1-\tau_{iRUM_{k_c}}\right)\right)\end{aligned} \quad \text{Eq. (3.15)}$$

In Eq. (3.13), if an attribute is selected as RUM, $\tau_{iRUM_k} = 1$, then the paired RRM parameter is equal to zero, $\tau_{iRRM_k} = \left(1-\tau_{iRUM_k}\right) = 0$. In other cases, if an attribute is selected as RRM, then $\tau_{iRUM_k} = 0$ and $\tau_{iRRM_k} = \left(1-\tau_{iRUM_k}\right) = 1$. Therefore, the actual draw of the structure selection parameter is the size of continuous attributes in a choice set. As $C_{\tau i}$ selected, individual-specific modified utility coefficients are drawn from multivariate normal.

$$\beta_i \sim MVN\left(C_{\tau i}\bar{\beta},\ C_{\tau i}V_{\beta}C_{\tau i}\right) \qquad \text{Eq. (3.16)}$$

To efficiently draw the individual-specific modified utility coefficient, the same technique used in Eq. (3.3) is also used in the same manner.

In Eq. (3.1), it is meaningless to use γ_i into the deterministic part of the utility, because even without γ_i, the excluded β_{ik} naturally converges to zero. However, the regret part of the modified utility converges to $\log(2)$ if $\beta_{ik_{RRM}} = 0$. Therefore, to reduce regret parts to zero, $\gamma_{ik_{RRM}}$ is multiplied in the regret part of the modified utility if regret structure is not selected [Eq. (3.17)].

$$\begin{aligned} MU_{itj} &= \sum_{k_{RUM} \in RUM} V_{k_{RUM}} + \sum_{k_{RRM} \in RRM} R_{k_{RRM}} \\ &= \sum_{k_{RUM} \in RUM} \gamma_{ik_{RUM}} \beta_{ik_{RUM}} X_{itjk_{RUM}} \\ &\quad + \sum_{k_{RRM} \in RRM} \gamma_{ik_{RRM}} \sum_{m \neq j} -\left[\log\left\{1 + \exp\left(\beta_{ik_{RRM}}\left(X_{itmk_{RRM}} - X_{itjk_{RRM}}\right)\right)\right\}\right] \end{aligned} \qquad \text{Eq. (3.17)}$$

As implied in Chorus et al., (2013), the modified utility has no identification problem with logit specification, and this dissertation used logit specification for the modified utility. Therefore, the equation for the choice model is shown in Eq. (3.18), and the error term ε_{itj} follows i.i.d. extreme value distribution.

$$RMU_{itj} = MU_{itj} + \varepsilon_{itj} \qquad \text{Eq. (3.18)}$$

The remainder of the specification is the same as Chapter 3.2 and is summarized as below.

$$\begin{aligned} V_{\beta}^{1/2} &\sim LKJCov\left(k, \eta, \varpi\right) \\ V_{\beta} &= \left(V_{\beta}^{1/2}\right)\left(V_{\beta}^{1/2}\right)^{T} \end{aligned} \qquad \text{Eq. (3.19)}$$

$$\begin{aligned} \beta_i &= C_{\tau i}\bar{\beta} + C_{\tau i}V_{\beta}^{1/2}\tilde{\beta}_i \\ \tilde{\beta}_i &\sim MVN\left(\mathbf{0}, I_K\right) = N\left(0,1\right)\cdot N\left(0,1\right)\cdot\ldots\cdot N\left(0,1\right) \\ \bar{\beta} &= \left(\bar{\beta}_1, \bar{\beta}_2, \ldots, \bar{\beta}_K\right) \end{aligned} \qquad \text{Eq. (3.20)}$$

$$\bar{\beta} \sim MVN\left(0, I\right) = N\left(0,1\right)\cdot N\left(0,1\right)\cdot\ldots\cdot N\left(0,1\right) \qquad \text{Eq. (3.21)}$$

$$\begin{aligned} \tau_{ik_{RUM}} &\sim Bernoulli\left(\theta_{ik_{RUM}}\right) \\ \tau_{ik_{RRM}} &= \left(1 - \tau_{ik_{RUM}}\right) \end{aligned} \qquad \text{Eq. (3.22)}$$

$$\begin{aligned} \theta_{ik_{RUM}} &\sim Beta\left(a, b\right) = Beta\left(\mu_{ik_{RUM}}, \phi_{ik_{RUM}}\right) \\ \mu_{ik_{RUM}} &= \frac{a}{a+b} = \text{logit}^{-1}\left(Z_i \cdot \zeta_{k_{RUM}}\right) \ or\ probit^{-1}\left(Z_i \cdot \zeta_{k_{RUM}}\right) \\ \phi_{ik_{RUM}} &= \frac{\sqrt{\mu_{ik_{RUM}}\left(1 - \mu_{ik_{RUM}}\right)}}{1 + a + b} \end{aligned} \qquad \text{Eq. (3.23)}$$

$$\zeta_{k_{RUM}} \sim MVN\left(z_{k_{RUM}}, \sigma_{z_{k_{RUM}}}\right) \qquad \text{Eq. (3.24)}$$

$$Likelihood = \prod_i \prod_t P_{itj}\left(X_{it} \mid \boldsymbol{\beta}_i, \boldsymbol{\gamma}_i\right) = \prod_i \prod_t \frac{\exp\left(MU_{itj}\right)}{\sum_m \exp\left(MU_{itm}\right)} \qquad \text{Eq. (3.25)}$$

$$\begin{aligned}
&P\left(V_\beta, \bar{\beta}, \tau, \theta, \zeta \mid Y, X, Z\right) \propto \\
&\quad L(Y \mid \beta) P\left(\beta \mid \bar{\beta}, \tau, \theta, \zeta\right) P(\theta \mid \zeta) P(\zeta) P\left(\bar{\beta}\right) P\left(V_\beta\right) \\
&\propto \left[\prod_i \prod_t \frac{\exp\left(\sum_{k_{RUM} \in RUM} \gamma_{ik_{RUM}} \beta_{ik_{RUM}} X_{itjk_{RUM}} + \sum_{k_{RRM} \in RRM} \gamma_{ik_{RRM}} \sum_{m \neq j} -\left[\log\left\{1 + \exp\left(\beta_{ik_{RRM}}\left(X_{itmk_{RRM}} - X_{itjk_{RRM}}\right)\right)\right\}\right]\right)}{\sum_{j'} \exp\left(\sum_{k_{RUM} \in RUM} \gamma_{ik_{RUM}} \beta_{ik_{RUM}} X_{itj'k_{RUM}} + \sum_{k_{RRM} \in RRM} \gamma_{ik_{RRM}} \sum_{j'' \neq j'} -\left[\log\left\{1 + \exp\left(\beta_{ik_{RRM}}\left(X_{itj''k_{RRM}} - X_{itj'k_{RRM}}\right)\right)\right\}\right]\right)}\right] \cdot \qquad \text{Eq. (3.26)} \\
&\left[\exp\left(-\frac{1}{2}\left(C_\tau\left(\boldsymbol{\beta} - \boldsymbol{\mu}_\beta\right)\right)' \left(C_\tau V_\beta C_\tau\right)\left(C_\tau\left(\boldsymbol{\beta} - \boldsymbol{\mu}_\beta\right)\right)\right)\right] \cdot \\
&\left[\frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \theta^{a-1}(1-\theta)^{b-1}\right] \cdot \\
&\left[\exp\left(-\frac{1}{2}\left(\zeta - \boldsymbol{\mu}_\zeta\right)' V_\zeta\left(\zeta - \boldsymbol{\mu}_\zeta\right)\right)\right] \cdot \\
&\left[\exp\left(-\frac{1}{2}\left(\bar{\beta} - b\right)'\left(\bar{\beta} - b\right)\right)\right] \cdot \left[\prod_k L_{kk}^{K-k+2\eta-2}\right]
\end{aligned}$$

3.4 Model Validation

This section validated the proposed models via synthetic data. For the purpose of validation, this dissertation generated synthetic data for each model and compared the results with baseline models. Also, the performance of the model was compared with log-likelihood of choice probability and information criterion: Widely Applicable Information Criterion, also known as Watanabe-Akaike

Information Criterion (WAIC) and Leave-One-Out Cross-validation (LOO).

3.4.1 Bayesian Model Fitness Measure: WAIC and LOO

WAIC and LOO are the measures for estimating out-of-sample pointwise prediction accuracy after the Bayesian inferencing models, which has the advantage over standard criteria such as AIC and BIC to calculate within-sample fits, except for more massive computation costs. (Gelman, Hwang, & Vehtari, 2014; Vehtari, Gelman, & Gabry, 2017)

WAIC is a Bayesian Criterion that estimates out-of-sample expectation. WAIC is a full Bayesian statistic that uses the entire posterior distribution, and it is asymptotically equal to LOO. WAIC uses the computed log pointwise posterior predictive density for measuring model fit and the effective number of parameters to penalty over-parameterization (Watanabe, 2010). The estimation of WAIC is simply described in Eq. (3.27). Watanabe (2010) suggested that WAIC is an asymptotically unbiased estimation of the out-of-sample prediction error. However, Gelman et al. (2014) suggested that in hierarchical models with weak prior information, the good characteristics of WAIC no longer hold.

$$WAIC = -2 \cdot \left(LPPD - P \right)$$

$LPPD$: log posterior predictive density

$$LPPD = \sum_i \log\left(mean\left(likelihood_i \right) \right)$$

P: effective number of free parpameters Eq. (3.27)

$$a_i = \log\left(mean\left(likelihood_i \right) \right)$$

$$b_i = mean\left(\log\left(likelihood_i \right) \right)$$

$$\mathrm{P} = \sum_i 2 \cdot \left(a_i - b_i \right)$$

Leave-One-Out Cross-Validation (LOO) is asymptotically equivalent to the Akaike Information Criterion in regular statistical models. LOO calculates leave-one-out predictive density without the *i*-th data point of given data [Eq. (3.28)]. PSIS-LOO (Pareto Smoothed Importance Sampling Leave-One-Out), which apply a Pareto distribution to smoothing procedure to important weights, which deducts more robustness in the finite case with weak priors compared to WAIC (Vehtari et al., 2017).

$$\begin{aligned} LOO &= \sum_i \log\left(p_{post(-1)}\left(y_i \right) \right) \\ &= \sum_i \log\left(\int p\left(y_i \mid \theta^{is} \right) p\left(\theta \mid y_{-i} \right) d\theta \right) \\ &= \sum_i \log\left(\frac{1}{S} \sum_{s=1}^{S} p\left(y_i \mid \theta^{is} \right) \right) \end{aligned} \qquad \text{Eq. (3.28)}$$

θ^{is} : posterior simulations

For the validation, the above two measures were used to compare model fit performance. Although WAIC has limitation in only being appropriate for finite samples and LOO is limited in that it relies on a subset, both models are appropriate for comparison in this dissertation.

3.4.2 Model validation (I): Heterogeneous Variable Selection Choice Model with Respondent Covariates

This section discusses the validity of a heterogeneous variable selection choice model with respondent covariates. For the purpose of comparison, HB mixed logit model and HB mixed logit with covariates model, Heterogeneous variable selection logit model (HVS Logit) (Gilbride et al., 2006) and the proposed model, (hereafter HVSC Logit) are estimated. Four measures of model fitness were estimated: log probability of choice (hereafter log-likelihood), target ratio, WAIC, and LOO. The target ratio is a matching ratio of variable selection, which counts as correct if the estimated selection variable is the same as the pre-assigned value of synthetic data. Experiments were conducted ten times to check consistency with different coefficient values. In repeated experiments, the model showed consistent results. This section reports one synthetic data to show the validity of the model. Specification of synthetic data is shown in Table 2.

The synthetic data consists of 300 samples, with 10 choice situations per

individual. The choice set consists of four alternatives with three attributes. Attributes and respondents' characteristics are drawn from standard Gaussian distribution. The utility coefficient betabar is arbitrarily assigned as 1,2,3. Individual utility coefficients are drawn from a multivariate normal distribution with the mean as betabar and variance-covariance as three by three identity matrix. Respondents' characteristics for variable 1 is 1, 2, variable 2 is 1, 3 and variable 3 is 2, 3. Then, the variable selection parameter is determined by inverse logit of the dot product of respondents' variable selection coefficient and respondents' characteristics. Lastly, individual utility coefficients are drawn from a multivariate normal distribution with the dot product of respondents' latent variable of variable selection and betabar. Therefore, the individual variable selection behavior is reflected in individual betas. With the same data, three models (HB (Mixed) Logit, HB (Covariates) Logit, HVS Logit and HVSC Logit) are estimated.

Table 2. Specification of the Synthetic Data (Model I)

Parameters	Specification
Number of samples (i)	300
Number of choice situation per individual (t)	10
Number of Alternatives (j)	4
Number of Attributes (k)	3
Attributes (X_{itjk})	$X_{itjk} \sim N(0,1)$
Respondents Characteristics (Z_i)	$Z_i \sim MVN(\mathbf{0}, I)$
Mean of individual utility coefficients $(\bar{\boldsymbol{\beta}})$	$\bar{\boldsymbol{\beta}} = (1,2,3)$
Respondents Variable Selection Coefficients (ζ)	$\zeta = \begin{bmatrix} 1 & 2 \\ 1 & 3 \\ 2 & 3 \end{bmatrix}$
Latent coefficient of variable selection $(\boldsymbol{\gamma})$	$\gamma_{ik} = \begin{cases} 1 & \text{invlogit}(\zeta Z_i) \geq .5 \\ 0 & o.w. \end{cases}$
Individual utility coefficients $(\boldsymbol{\beta}_i)$	$\boldsymbol{\beta}_i \sim MVN(C_{\gamma_i}\bar{\boldsymbol{\beta}}, C_{\gamma_i}\mathbf{I}C_{\gamma_i})$

Table 3. Model Fit Comparison (Model I)

	LogProb (LL) (higher, better) (S.D.)	Target (higher, better)	WAIC (lower, better) (S.E.)	LOO (lower, better) (S.E.)
HVSC Logit	-681.47 (15.58)	97.1%	1476.57 (48.93)	1518.06 (49.89)
HVS Logit	-684.23 (19.04)	93.8%	1529.64 (49.85)	1595.55 (51.43)
HB (Mixed) Logit	-769.12 (23.80)		1965.44 (61.49)	2122.59 (64.78)
HB (Covariate) Logit	-767.97 (25.14)		1966.79 (61.59)	2127.09 (64.65)

In the hypothetical situation, The suggested model shows good performance above all models, in the most measures that I considered (Table 3). In perspective of prediction, log-likelihood of choice probability is almost similar but slightly lower in HVSC Logit model compare to the HVS Logit model. However, other trials show slightly better performances on it. Both HVS Logit and HVSC Logit model shows significant better log probability than HB Logit model. Target rate of HVSC Logit model (97.1%), which identify variable selection, shows higher prediction than HVS Logit model (93.8%). Both of WAIC and LOO of HVSC Logit shows better performance compare to HVS Logit. For the comparison of hierarchical Bayesian models, LOO is a more suitable measure (Vehtari, Gelman, & Gabry, 2015). Loo shows more difference in HVSC Logit and HVS Logit model.

Table 4. Comparison of Information Criterion - WAIC (Model I)

	WAIC	pWAIC	dWAIC	weight	SE	dSE
HVSC Logit	1476.57	88.52	0	0.96	48.93	0
HVS Logit	1529.64	125.26	53.07	0.04	49.85	13.85
Mixed Logit	1965.44	332.41	488.87	0	61.49	31.86
HB Logit	1966.79	334.99	490.22	0	61.59	32.45

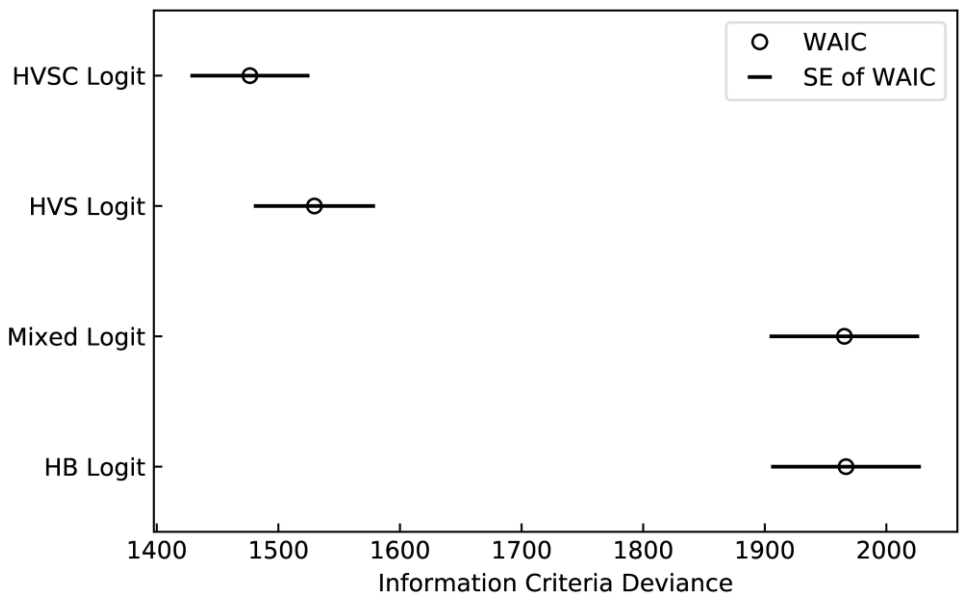


Figure 6. Comparison Diagram of WAIC (Model I)

Table 5. Comparison of Information Criterion - LOO (Model I)

	LOO	pLOO	dLOO	weight	SE	dSE
HVSC Logit	1518.06	109.27	0	0.97	49.89	0
HVS Logit	1595.55	158.21	77.49	0.03	51.43	15.73
Mixed Logit	2122.59	410.98	604.53	0	64.78	35.32
HB Logit	2127.09	415.14	609.03	0	64.65	35.58

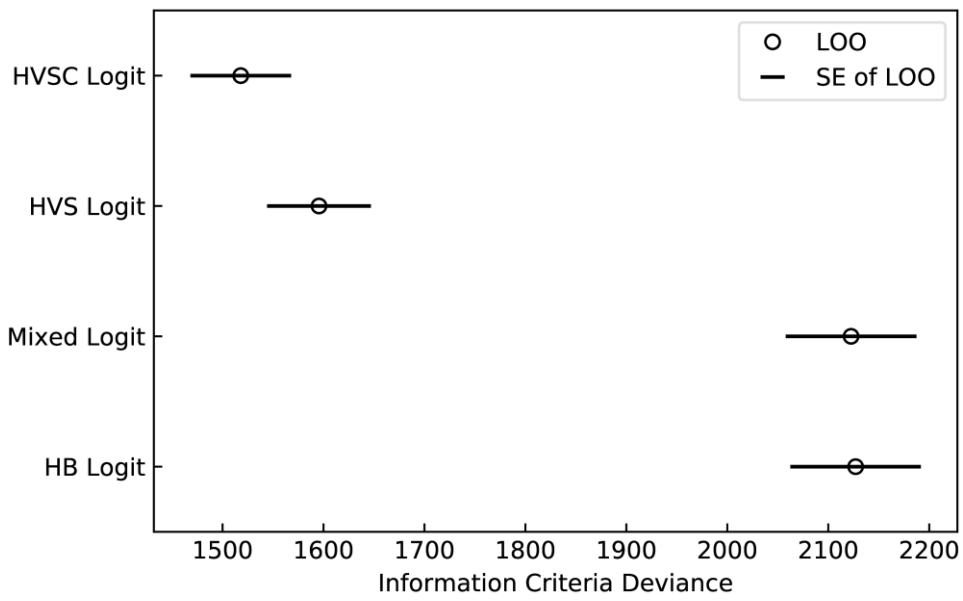


Figure 7. Comparison Diagram of WAIC (Model I)

More details on WAIC (Table 4) and LOO (Table 5) comparisons are suggested in the tables above. Akaike weights (fourth column of each table) are used in model comparison. The presented Akaike weights indicate 0.91 weights on HVSC Logit in WAIC and 1 weight on HVSC Logit in LOO, and also shows that the suggested model is appropriate. The penalty measure (second column of each table, pWAIC, and pLOO) shows that the lowest values on the HVSC Logit model. This also suggested that an increment of parameters leads to a more accurate estimation.

Simulation results show no covariance structures on HVSC Logit. Although the synthetic data did not assume covariance structure on utility coefficients, HVS Logit and HB Logit estimated significant covariance parameters. Due to the elimination of an unnecessary covariance, accurate, and unbiased estimation results were obtained in HVSC Logit model.

Table 6. Simulation Results with Synthetic Data

	HVSC Logit			HVS Logit			HB Logit			True Value
	Mean		S.D.	Mean		S.D.	Mean		S.D.	
Betabar_0	3.549	*	0.434	3.248	*	0.742	1.122	*	0.181	1.000
Betabar_1	7.419	*	0.507	6.878	*	0.567	2.985	*	0.291	2.000
Betabar_2	9.985	*	0.427	8.328	*	0.661	4.086	*	0.379	3.000
Theta_0				0.383	*	0.040				0.446
Theta_1				0.552	*	0.037				0.48
Theta_2				0.560	*	0.037				0.493
dBeta_0_0	0.980	*	0.122							1
dBeta_0_1	1.796	*	0.129							2
dBeta_1_0	0.804	*	0.114							1
dBeta_1_1	1.940	*	0.114							3
dBeta_2_0	0.959	*	0.109							2
dBeta_2_1	1.685	*	0.105							3
Sigma_0_0	43.646	*	9.909	66.905	*	24.261	7.614	*	1.391	
Sigma_0_1	8.962		14.934	17.112		14.980	-0.293		0.813	
Sigma_0_2	-0.220		4.137	-1.283		22.104	-0.681		1.022	
Sigma_1_1	26.546	*	5.655	33.262	*	8.497	15.917	*	2.805	
Sigma_1_2	-2.444		2.484	-24.036		11.280	-4.640	*	1.582	
Sigma_2_2	2.261	*	1.740	42.262	*	13.987	28.865	*	4.890	
bprecision	9.687	*	0.289							
Choicelogp	-869.423		14.844	-857.153		17.235	-985.600		25.260	
Target	97.1%			93.8%						
WAIC	1851.57			1900.05			2453.28			
LOO	1901.61			1977.93			2600.86			

* Significance at the 1% levels

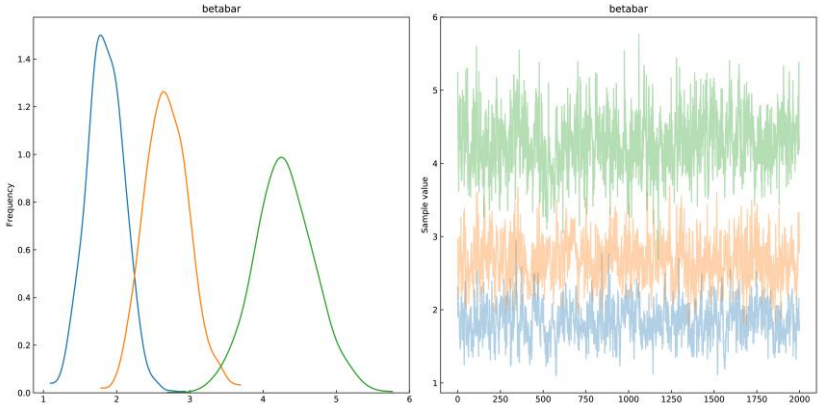


Figure 8. Density Plot and Trace Plot of HB Logit Model

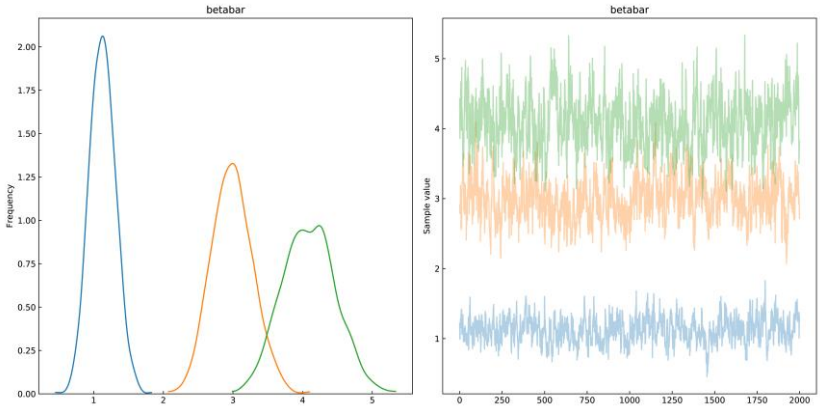


Figure 9. Density Plot and Trace Plot of HVS Logit Model

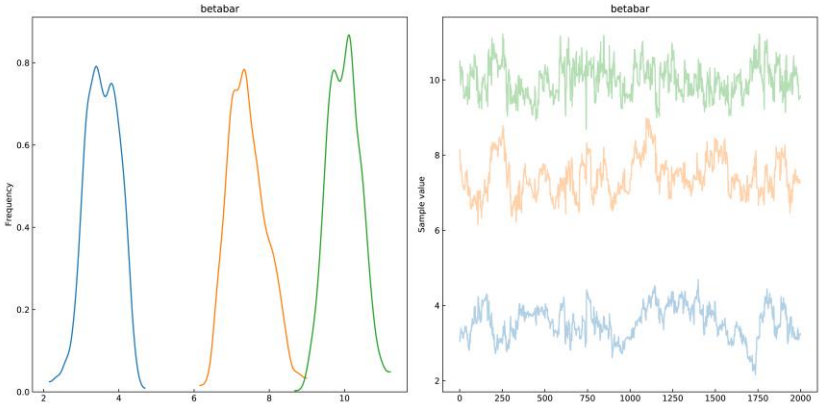


Figure 10. Density Plot and Trace Plot of HVSC Logit Model

3.4.3 Model validation (II): Heterogeneous Choice Model for Respondent Decision Heuristics Strategy

This section discusses the validity of heterogeneous choice model for respondent decision heuristics strategy. For the purpose of cross-validation, HB random utility maximization model (hereafter RUM), HB random regret minimization model (hereafter RRM), Heterogeneous choice model for respondent decision heuristic strategy between RUM and RRM (hereafter HDH RUM-RRM) and Heterogeneous choice model for respondent decision heuristic strategy with covariates between RUM and RRM (HDH Cov. RUM-RRM) are estimated. Similar to Section 3.5.2., four measures of model fitness were estimated: log probability of choice (log-likelihood), target ratio, WAIC, and LOO. The target ratio is matching ratio of model selection, which counts as correct if the estimated selection is same with pre-assigned structure between RUM and RRM of synthetic data. Experiments were also conducted ten times to check consistency with different coefficient values. In repeated experiments, the model showed consistent results. This section reports one synthetic data to show the validity of the model. Specification of synthetic data is shown in Table 7.

Table 7. Specification of Synthetic Data (Model II)

Parameters	Specification
Number of samples (i)	300
Number of choice situation per individual (t)	10
Number of Alternatives (j)	4
Number of Attributes (k)	3 (a dummy attribute, two continuous attributes)
Attributes (X_{itjk})	$X_{itjk} \sim N(0,1)$
Respondents Characteristics (Z_i)	$Z_i \sim N(0,1)$
Mean of individual utility coefficients $(\bar{\boldsymbol{\beta}})$	$\bar{\boldsymbol{\beta}} = (\bar{\boldsymbol{\beta}}_{dummy}, \bar{\boldsymbol{\beta}}_{conti-RUM}, \bar{\boldsymbol{\beta}}_{conti-RRM})$ $\bar{\boldsymbol{\beta}}_{dummy} = (1), \bar{\boldsymbol{\beta}}_{conti-RUM} = (2,3),$ $\bar{\boldsymbol{\beta}}_{conti-RRM} = (2,3)$
Individual utility/regret coefficients $(\boldsymbol{\beta}_i)$	$\boldsymbol{\beta}_i \sim MVN(\bar{\boldsymbol{\beta}}, V_\beta)$
Respondents Characteristics Coefficients (ζ)	$\zeta = \begin{bmatrix} 1 & 3 \\ 2 & 2 \end{bmatrix}$

Table 8. Model Fit Comparison (Model II)

	LogProb (LL) (higher, better) (S.D.)	Target (higher, better)	WAIC (lower, better) (S.E.)	LOO (lower, better) (S.E.)
HDH Cov. RUM-RRM	-454.607 (20.304)	80.30%	1191.40 (49.64)	1260.50 (52.13)
HDH RUM-RRM	-464.109 (22.117)	60.00%	1220.79 (46.07)	1291.15 (49.03)
RUM	-557.392 (20.084)		1397.27 (61.54)	1444.57 (63.16)
RRM	-1021.406 (21.993)		2306.34 (78.10)	2332.01 (79.96)

Overall performance measures showed better performance for the proposed model, HDH Cov. RUM-RRM. In terms of prediction, log-likelihood of choice probability in the HDH Cov. RUM-RRM model is slightly higher than the HDH RUM-RRM model, but not statistically significant. The target ratio, which measures whether the respondents have the RUM structure or the RRM structure, was found to be significantly higher in HDH Cov. RUM-RRM model, which means that sociodemographic characteristics help finding consumer decision structure heterogeneity. WAIC and LOO each show the lowest values on the HDH Cov. RUM-RRM model.

Table 9. Comparison of Information Criterion - WAIC (Model II)

	WAIC	pWAIC	WAIC difference	AWeight	S.E.	S.E. difference
HDH Cov. RUM-RRM	1191.4	217.58	0 (base)	0.65	49.64	0 (base)
HDH RUM-RRM	1220.79	226.51	29.39	0.21	46.07	25.82
RUM	1397.27	225.38	205.87	0.14	61.54	47.1
RRM	2306.34	218.34	1114.94	0	78.1	66.94

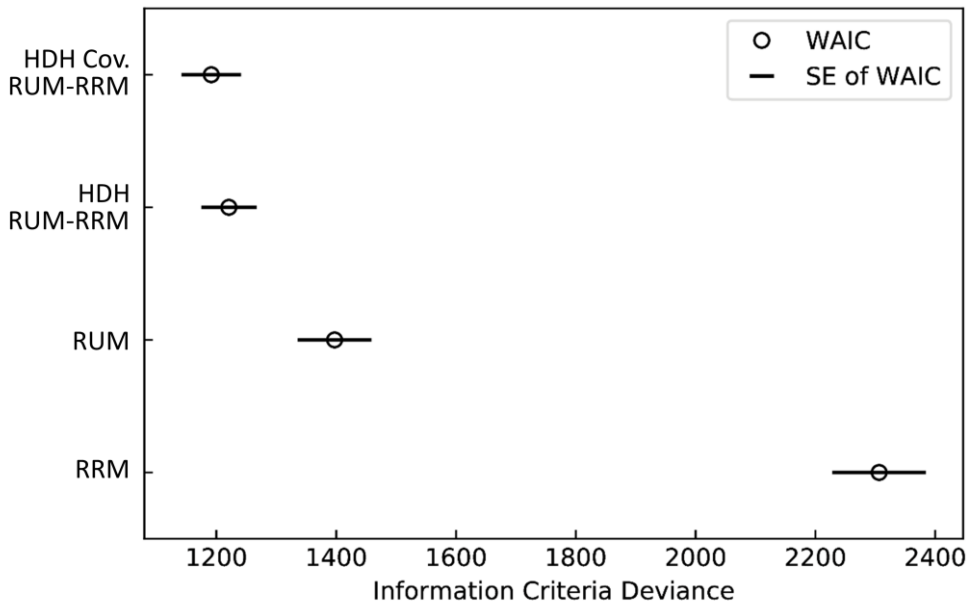


Figure 11. Comparison Diagram of WAIC (Model II)

Table 10. Comparison of Information Criterion - LOO (Model II)

	LOO	pLOO	LOO difference	Aweight	S.E.	S.E. difference
HDH Cov. RUM-RRM	1260.5	252.14	0 (base)	0.61	52.13	0 (base)
HDH RUM-RRM	1291.15	261.69	30.64	0.18	49.03	26.95
RUM	1444.57	249.03	184.07	0.22	63.16	48.56
RRM	2332.01	231.17	1071.5	0	79.96	67.82

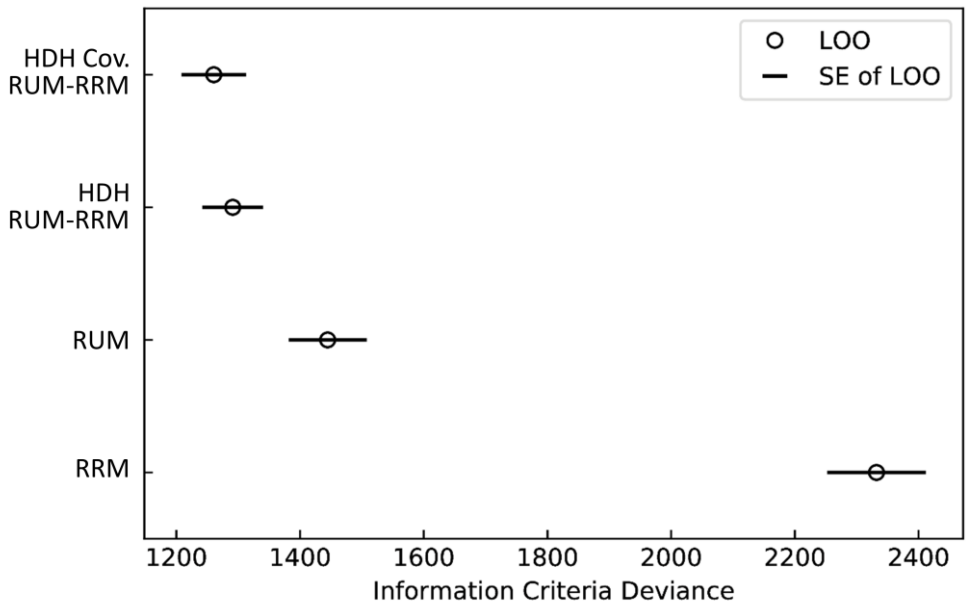


Figure 12. Comparison Diagram of LOO (Model II)

Table 11. Simulation Results with Synthetic Data (Model II)

	HDH Cov. RUM-RRM		HDH RUM-RRM		RUM		RRM		
Variables	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	True Value
(Dummy)									
Beta_0	1.611*	0.155	1.653*	0.163	1.568*	0.160	0.929*	0.104	1
(RUM)									
Beta_1	4.55*	0.298	4.834*	0.326	4.799*	0.238			2
Beta_2	6.819*	0.363	6.678*	0.405	6.756*	0.322			3
(RRM)									
Beta_1'	4.084*	0.298	3.828*	0.287			2.278*	0.139	2
Beta_2'	3.926*	0.292	3.819*	0.328			2.098*	0.131	3
(Beta_1)									
dBeta_1_0	0.678*	0.181							1
dBeta_1_1	1.971*	0.256							3
(Beta_2)									
dBeta_2_0	0.475*	0.176							2
dBeta_2_1	1.590*	0.216							3
Theta_1			0.498*	0.052					0.486
Theta_2			0.723*	0.039					0.510
Sigma_0_0	1.083*	0.547	1.047*	0.480	1.546*	0.575	0.368*	0.208	
Sigma_0_1	0.077	0.392	0.384	0.397	0.042	0.373	0.154	0.134	
Sigma_0_2	0.012	0.274	-0.039	0.257	0.162	0.386	0.223	0.127	
Sigma_0_3	-0.175	0.312	-0.266	0.345					
Sigma_0_4	-0.072	0.218	-0.078	0.193					
Sigma_1_1	3.062*	1.195	1.744*	0.847	2.250	0.545	0.970*	0.259	
Sigma_1_2	-0.311	0.473	-0.025	0.289	-0.615	0.387	0.375*	0.149	
Sigma_1_3	0.038	0.663	-0.173	0.505					
Sigma_1_4	-0.052	0.371	-0.074	0.254					
Sigma_2_2	0.920*	0.796	0.573*	0.607	1.458*	0.658	0.790*	0.197	
Sigma_2_3	-0.046	0.300	-0.060	0.286					
Sigma_2_4	-0.029	0.189	-0.002	0.147					

(Continuous of Table 8)

Variables	Mean	S.E.	Mean	S.E.	Mean	S.E.	Mean	S.E.
Sigma_3_3	1.256*	0.675	1.469*	0.622				
Sigma_3_4	0.170	0.348	0.188	0.311				
Sigma_4_4	0.383*	0.478	0.353	0.401				
precision	8.506	1.039						
Choicelogp	-454.600	20.304	-464.110	22.117	-557.392	20.084	-1021.406	21.993
Target	80.30%		60.00%					
WAIC	1191.40	49.64	1220.79	46.07	1397.27	61.54	2306.34	78.10
LOO	1260.50	52.13	1291.15	49.03	1444.57	63.16	2332.01	79.96

* Significance at the 1% levels

The main difference between the HDH Cov. RUM-RRM and the HDH RUM-RRM model is the target ratio. Without the respondents' characteristics, the target ratio is quite lower in the HDH RUM-RRM model. In Akaike Weights (fourth column of Table 9 and Table 10), no criterion weights on RRM model, although within sample RRM structure is assumed. RUM and HDH RUM-RRM gets small Akaike weights, and HDH Cov. RUM-RRM model gets majority weights on both criterions. Therefore, it is conclusive that the suggested HDH Cov. RUM-RRM is acceptable, and the model validity is obtained.

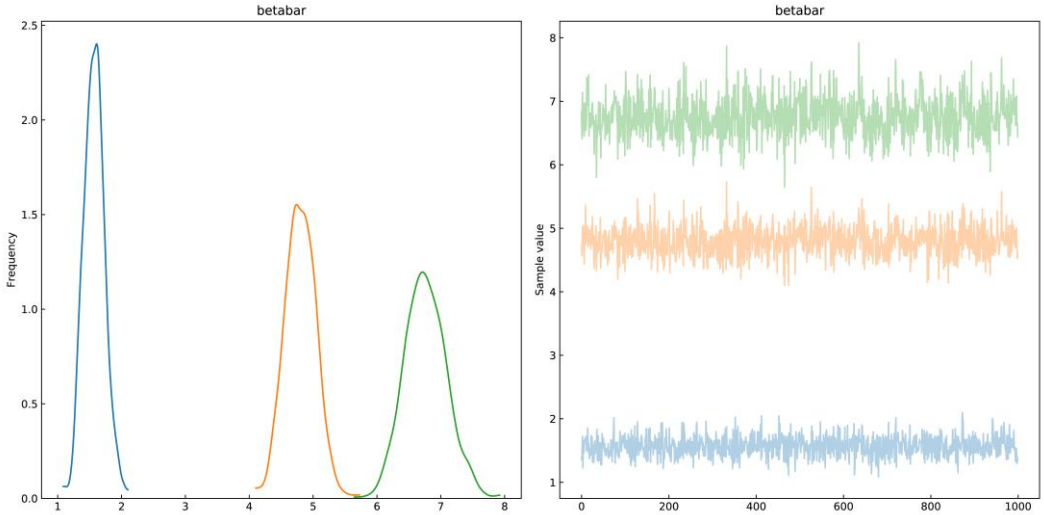


Figure 13. Density Plot and Trace Plot of RUM

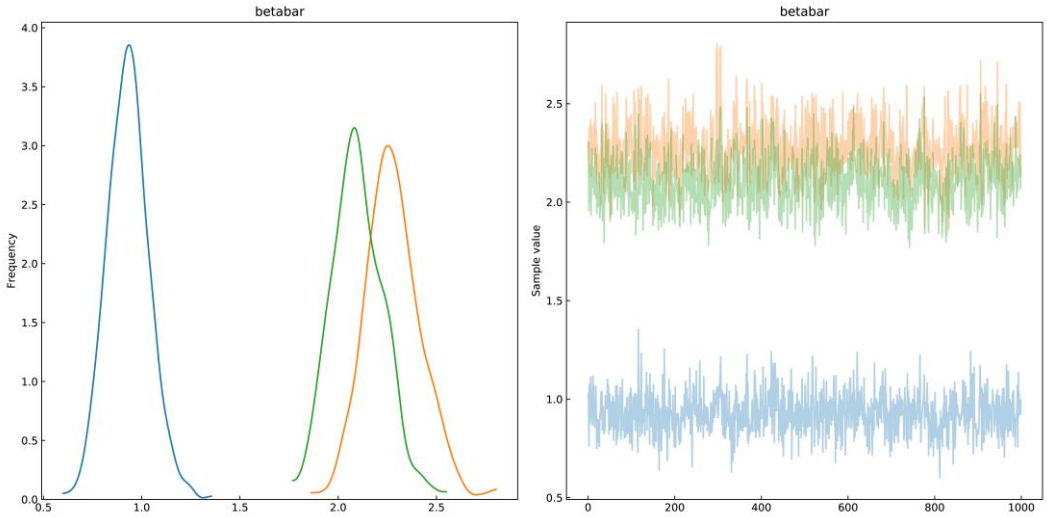


Figure 14. Density Plot and Trace Plot of RRM

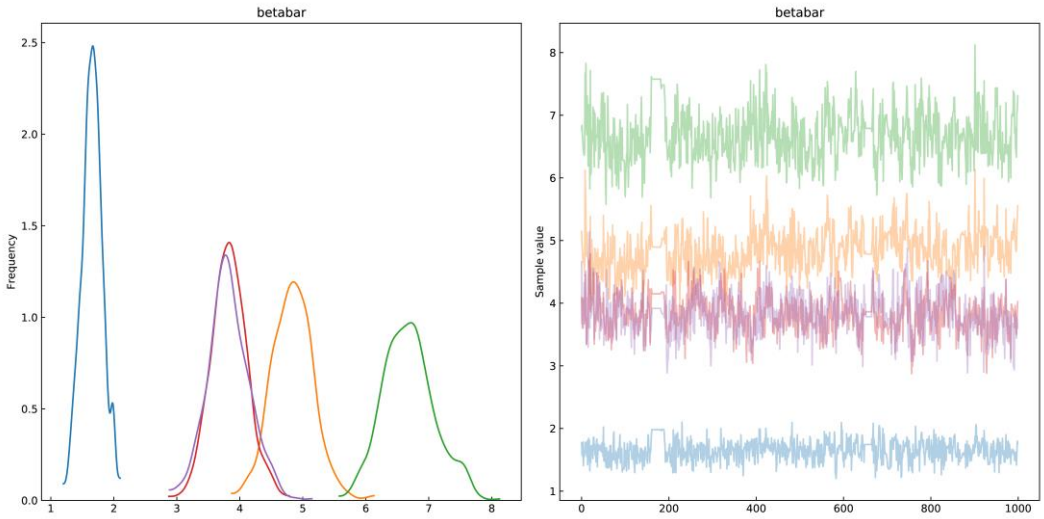


Figure 15. Density Plot and Trace Plot of HDH RUM-RRM

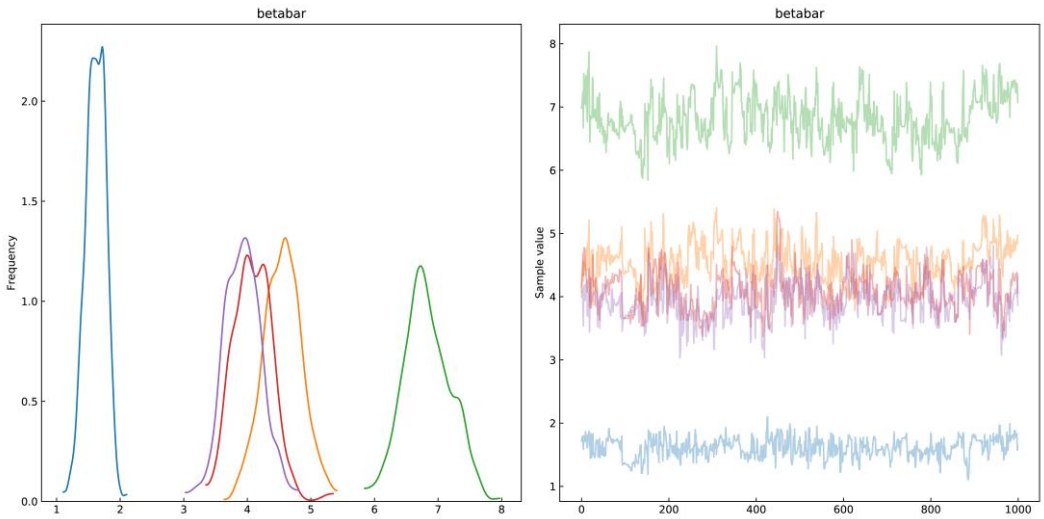


Figure 16. Density Plot and Trace Plot of HDH Cov. RUM-RRM

Chapter 4. Empirical Studies

4.1 The Study on Consumer Choice Behaviors in High-Tech Goods 1 – Zero Energy House (ZEH)

This section reports the empirical results of the suggested models in zero energy house choice behavior. The proposed two models and baseline reference models are estimated, and the results of these models are reported in Appendix 3. This section discusses the empirical results of suggested models and information criterion of the models.

4.1.1 Introduction

Many developed countries have been setting up the objectives to cope with climate change and established energy policy to reduce greenhouse gas (GHG) and incorporate energy demand management. Korea is the fifth-highest country in energy consumption and sixth-highest country in GHG emission among OECD. In November 2009, the Korean government officially announced that a voluntary mid-term goal of greenhouse gas emission reduction, 30% of the business-as-usual (BAU) (Korea Ministry of Environment, 2015b). After the United Nations Climate Change Conference at Paris on June 30, 2015, Korea decided to reduce

37% of the 2030 emissions forecast (BAU, business-as-usual) of 850.6 million ton of CO2 (Korea Ministry of Environment, 2015a) and announced it INDC (Intended Nationally Determined Contribution). However, many were unsure about whether Korea could reach carbon emission reduction targets at home and abroad. These skepticisms were due to the uncertainty of overseas treatment, which accounts for a third of the total reduction target. Korea's Ministry of Environment announced a new energy consumption reduction strategy that covers practical measures[1] in various industrial fields including the industrial sector, building sector, transportation sector, waste sector, and power generation sector (Korea Ministry of Environment, 2018).

According to the IPCC, GHG emissions from building accounts for about 19% of total emissions, trailing industrial sector's 31%. Of the carbon emissions from the building, 53% of the total emissions are from residential buildings (T. Kim, 2017). Also, Choi (2016) noted that energy consumption in the building sector accounts for 19% of the total energy consumption in Korea. The implementation

[1] (Common) Expansion of energy demand management by sector, insulation of cooling and heating, improvement of equipment efficiency, improvement of old facilities
(Conversion Division) The 8th Electricity Supply and Demand Plan, which includes comprehensive measures to reduce fine dust, including the early closure of aged coal power plants
(Industrial sector) Improvement of energy utilization efficiency by industry sector, improvement of industrial process, replacement with environment-friendly raw materials and fuel, high efficiency reduction technology, substitution of greenhouse gas refrigerant, carbon capture and storage utilization technology, etc.
(Building division) Strengthening the approval standards for new buildings, green remodeling of existing buildings, finding business models related to urban regeneration, and expanding renewable energy supply
(Transportation) Expansion of eco-friendly cars, strengthening automobile fuel efficiency standards, improving fuel efficiency of ships and aircraft
(Waste sector) Reduction of waste by source, workplace, construction, etc. Reduction of recycling, recycling, minimization of landfill, methane capture and resources

of zero energy building can be a crucial solution to resolve energy security problems. Therefore, demand management of the residential building is one of the critical issues in energy demand management and carbon emission sector. Consumer acceptance analysis is needed for the successful policy implementation.

A zero-energy building is a residential or commercial building that has improved energy efficiency and renewable energy generation facility to fulfill its energy demand on its own (Torcellini, Pless, Lobato, & Hootman, 2010). In order to achieve reasonable level of energy efficiency, zero energy buildings are constructed to minimize energy loss by installing insulation or energy-efficient facility and to generate energy through the installation of renewable energy facility for energy self-sufficiency. However, in reality, zero energy buildings are constrained by technological constraints and capital constraints. Installing such apparatus must entail an increase in construction costs; and many construction firms are unfavorable toward such cost increase. Even if the government provides subsidies, if consumer acceptance cannot accommodate this cost increase, implementation of the zero-energy policy will be difficult. Therefore, this section focuses on the consumer acceptance of zero energy house (ZEH). Through the analysis of consumer acceptability, this dissertation intended to derive the acceptability of zero energy house via suggested methodology.

Since the zero energy house has both environmental and residential attributes, both factors must be considered. In order to simplify each characteristic as simple

as possible, the survey contained the most important factors of many residential properties, accessibility, and property of large construction companies. There are many properties in the residential property (area, number of floors, school district, residential environment, house orientation, interior materials, accessory facilities, and so forth) In order to show them implicitly, the survey was contained accessibility (including locality, environment, school district, etc.) and large construction companies (premium apartments; interior materials and accessories).

In order to express environmental attributes, in short, the survey included the reduction of utility costs (directly related energy usage reduction) and reduction of carbon emissions. Besides, many studies have implied the NIMBY phenomenon for the installation of solar panels, so the survey included the attributes of installing solar panels to observe the acceptance.

The attributes related to the residential property are reflected in the market price. For sensitivity check, marginal willingness to pay for a significant firm brand apartment is estimated as 1.2 million won per 3.3m^2. This result is consistent with the market price of major firm brand apartment. The market price difference between brand apartment and small and medium firm apartment is in between 0.8 million won per 3.3m^2, and 3.5 million won per 3.3m^2. As the amount of willingness-to-pay and the market price form a similar price, it can be confirmed that the attribute level and alternative setting of this questionnaire are appropriately formed and reflect the consumers' preferences.

4.1.2 Data Descriptions

For empirical analysis, this dissertation collected data from the hypothesized conjoint survey. The survey was performed in March and April, 2019, and conducted face-to-face interviews by Gallup Korea. A total of 701 households participated in the survey, who populated in Seoul and metropolitan area and five major cities (Busan, Incheon, Daegu, Daejeon, and Gwangju). The interviewees were chosen by probability sampling with a quota to have representative demographic characteristics.

The survey processed as follows. First, interviewees were asked about their sociodemographic information such as gender, age, residential area, and so forth. Then, the interviewer asked about the respondents' level of awareness about technology and the environment. Afterwards, the interviewer described the attribute and its level in the conjoint questionnaire and the interviewee choose an alternative in conjoint sets. The descriptive statistics of socio-demographic characteristics of survey respondents are shown in Table 12 and continuous characteristics of socio-demographic characteristics are described in Table 13. Descriptions and levels of attributes in the conjoint surveys are shown in Table 14. The ratio of the respondents represents Korean residents, in terms of gender, age, residential area, and residential type (Table 12).

Table 12. Socio-Demographic Characteristics of the ZEH Survey Respondents

Category	Group	Frequency	Percent
Gender	Male	353	50.36
	Female	348	49.64
Family Number	1	78	11.13
	2	72	10.27
	3	140	19.97
	4	352	50.21
	5>	59	8.42
Residential Area	Metropolitan Area (near Seoul)	350	49.93
	Else	351	50.07
Age	20s	163	23.25
	30s	167	23.82
	40s	183	26.11
	50s	188	26.82
Residential Type	Apartment (Complex)	238	33.95
	Apartment (Small)	158	22.54
	Etc (Detached, Studio)	307	43.79
Commute	> 1hr	84	11.98
	1 hr – 2 hr	389	55.49
	2 hr – 3 hr	209	29.81
	<3 hr	19	2.71
Ownership Type	Home Owner & Secured	642	91.58
	Pay Rent	59	8.42
Total		701	

Table 13. Descriptive statistics of Continuous Variables

	Mean	Std. Dev.

Average Heat Costs (Unit: 1,000 KRW)	124.9	52.755
Eco Perception	3.499	0.49
High-Tech Perception	3.996	0.447

Table 14. Attributes in ZEH Conjoint Cards

Attribute	Description	Level
	(Dummy Attributes)	
Major Firm	Whether ZEH is built by a construction conglomerate	Middle and small (baseline) Major Conglomerate
Renewable	Whether to install a renewable energy generating facility such as a geothermal or solar panel for energy produce.	Not Installing (baseline) Installing
Vent Type	the air quality and energy efficiency vary among vent type, Natural ventilation by opening windows, Mechanical ventilation that help maintain air quality and Heat recovery ventilation that help maintain air quality and reduce energy use.	Natural Ventilation (baseline) Mechanical ventilation Heat Recovery Ventilation
	(Continuous Attributes)	
Access Time	Walking distance to schools and public transports.	5minute by walking (500M) 10minute by walking (1KM) 15minute by walking (1.5KM)
Reduction of CO_2 emission (Co2 Reduction)	CO_2 emission reduction per a household	30% (1.2tonCO_2 per year) 60% (4.8tonCO_2 per year) 90% (8.4tonCO_2 per year)
Utility Cost Saving (Cost Save)	Percentage of cost-saving of energy use such as lighting, heating, cooling in a Zero Energy Apartment.	Save 30% Save 60% Save 90%
Cost (Cost)	Price increase per 3.3m^2 (1 py) compared to the current residential apartment	1,000,000KRW increase 2,000,000KRW increase. 3,000,000KRW increase

The conjoint survey used in this dissertation includes major firm, renewable, ventilation type, access time, reduction of CO2 emission, heat cost (energy) saving and cost increase as attributes of zero energy house (Table 14). Such attributes are selected after careful review of previous literature.

In the case of Korea, the brand value of apartments built by large construction conglomerate is higher than mid-sized construction firms (Hwang & Lee, 2015). These brand values are reflected in apartment sales prices and real estate transaction prices. The brand value is measured with the major firm attribute. In addition to the characteristics of zero energy building, accessibility is a factor that has great impact on consumers' choice of a residential building. Through the time taken to the main facilities, such as school and transportation station, the attribute of accessibility of the building is evaluated via walking through 5minutes (approximately 0.5KM), 10minutes (approximately 1.0KM) and 15minutes (approximately 1.5KM) (Louviere & Timmermans, 2010; Zondag & Pieters, 2005).

Renewable energy must be installed to achieve the goal of zero energy house. However, there are prior studies that insist the degradation of consumer acceptance of landscaping due to the installation of renewable energy (Zoellner, Schweizer-Ries, & Wemheuer, 2008). Installing a PV panel may cause damage such as inhibiting landscape and interference with reflected sunlight. Therefore,

the conjoint survey includes renewable energy installation attributes to understand the preference of respondents toward installing renewable in the apartment complex.

Installation of Ventilation is also included since ventilation is one of the essential features of zero energy buildings, keeping air quality and temperature at a consistent level. The three options are included; natural ventilation (baseline), mechanical ventilation, and heat recovery ventilation. Although mechanical ventilation is relatively cheap, it is simply a device to maintain air quality. Heat recovery ventilation can ensure air quality and homeostasis at room temperature but is quite expensive. To improve energy efficiency from heating or cooling, zero energy buildings must be equipped with heat recovery ventilation. Therefore, the three options of ventilation are included.

And then, the survey included amount of CO2 reduction per year. Due to high energy efficiency of zero energy building, carbon emissions from zero energy will be reduced compared to conventional buildings. To find out consumers' utility toward reducing carbon emission, the survey included reduction of CO2 emission about 1.2 ton CO2 per year, 4.8 ton CO2 per year and 8.4 ton CO2 per year.

Besides homeostasis, the essential benefit of zero energy house is reduction of utility (heat and electricity) cost. High energy efficiency and energy generation facility contribute significantly to the reduction of utility costs. Also, the reduction of utility measures energy efficiency simultaneously. Therefore, three-level of heat

cost saving is included as 30% reduction, 60% reduction, and 90% reduction.

As mentioned earlier, construction of zero energy house is accompanied by an increase in costs. According to the Korea Ministry of Land, Infrastructure, and Transportation (2018), the construction cost must increase by at least 30%. Therefore, the cost is suggested in three levels, 1,000,000 KRW increase per 3.3m^2 (about 933 USD) [2], 2,000,000 KRW increase per 3.3m^2 (about 1,866 USD) and 3,000,000 KRW increase per 3.3m^2 (about 2,799 USD).

4.1.3 Empirical Results

This section reports the analysis results about consumer zero energy house choice behavior via two proposed models. Heterogeneous variable selection behavior of bundling choice with respondents' socio-demographic characteristics (Attribute Non-Attendance behavior) and exploring heterogeneous decision-making strategy with respondents socio-demographic characteristics. Section 4.1.3.1 reports heterogeneous variable selection behavior and section 4.1.3.2 reports heterogeneous decision-making strategy behavior.

[2] the rate of currency is based on 03-20-2019 KRW-USD rate, which is the starting date of survey, 1071.82KRW/USD
https://ko.exchange-rates.org/HistoricalRates/P/USD/2018-03-20

4.1.3.1 Heterogeneous Variable Selection Behavior of ZEH

This section reports heterogeneous variable selection behavior on zero energy house choice situation. The result of the HVSC Logit is shown in Table 15. Full comparison of HB (Mixed) Logit and HVS Logit is included in Appendix 5. In all three models, sample level utility coefficients were in the same direction, excepts for non-significance utility coefficients. Log-likelihood of HVSC Logit (-1678.0) showed the lowest level among the three models (HVS Logit: -1613.2, Mixed Logit: -1655.3) and HVS Logit model shows the highest log-likelihood among the three models. However, both information criterion (WAIC and LOO) indicates empowering HVSC Logit model.

Table 15. Empirical Result of HVS Behavior with Covariates on ZEH

Utility Coefficients				Variable Selection Coefficients			
	Mean		S.D.		Mean		S.D.
Major Firm	2.331	***	0.288	Constant	-0.639	***	0.341
				Seoul	1.540	***	0.225
				APT	0.700	***	0.216
				Home Owner	-1.795	***	0.525
				Family	-0.118		0.120
				University	0.127		0.199
				High Tech Perception	-0.349	***	0.135
				Eco Perception	0.477		0.361
				Utility Cost	0.267	**	0.099
				Commute	-0.109	**	0.069

				Home price>5	1.014	***	0.458
Renewable	-0.158		0.137	Constant	-0.145		0.381
				Seoul	-0.068		0.379
				APT	0.723	***	0.271
				Home Owner	-1.375	**	0.539
				Family	0.766	***	0.219
				University	0.440	*	0.221
				High Tech Perception	-0.631	***	0.180
				Eco Perception	0.211	*	0.259
				Utility cost	0.020		0.328
				Commute	-0.485	*	0.261
				Home price>5	-0.395	*	0.354
Mechanical Vent	-0.030		0.166	Constant	0.729	**	0.361
Heat Exchange Vent	-0.680	***	0.208	Seoul	-0.344		0.360
				APT	-1.635	**	0.693
				Home Owner	0.342		0.544
				Family	-0.561	***	0.091
				University	0.101		0.348
				High Tech Perception	0.638	**	0.240
				Eco Perception	-0.381	***	0.081
				Utility Cost	0.034		0.137
				Commute	0.004		0.123
				Home price>5	-0.253		0.268
Access Time	-1.442	***	0.266	Constant	0.081		0.725
				Seoul	-1.168	***	0.152
				APT	0.180		0.278
				Home Owner	-0.152		0.414
				Family	0.332	**	0.148
				University	-0.775	***	0.276
				High Tech Perception	-0.399	***	0.084
				Eco Perception	0.644	***	0.140

				Utility Cost	-0.209		0.172
				Commute	0.494	***	0.100
				Home price>5	-0.274		0.449
CO_2 Reduction	0.460	***	0.069	Constant	-0.910	**	0.356
				Seoul	1.669	***	0.330
				APT	0.621	***	0.206
				Home Owner	-0.207		0.503
				Family	-0.750	*	0.459
				University	-0.203		0.339
				High Tech Perception	0.413	***	0.183
				Eco Perception	-0.132		0.235
				Utility Cost	0.365	***	0.113
				Commute	-0.101		0.105
				Home price>5	-1.283	***	0.238
Utility Cost Reduction	1.550	***	0.113	Constant	0.914	*	0.536
				Seoul	1.028	***	0.277
				APT	0.184		0.233
				Home Owner	-0.884	**	0.376
				Family	0.427	***	0.179
				University	-0.378		0.327
				High Tech Perception	0.535	***	0.172
				Eco Perception	-0.490	***	0.198
				Utility Cost	-0.080		0.095
				Commute	-0.112	*	0.134
				Home price>5	0.972	**	0.346
Cost	-1.851	***	0.273	Constant	0.827	**	0.312
				Seoul	-0.670	***	0.229
				APT	-0.651	**	0.240
				Home Owner	0.304	*	0.277
				Family	0.363	***	0.111
				University	0.012		0.207

				High Tech Perception	0.007		0.106
				Eco Perception	-0.854	***	0.125
				Utility Cost	-0.974	***	0.118
				Commute	-0.093		0.184
				Home price>5	-0.475		0.376
No Choice	-3.314	***	0.350	Constant	-1.707	***	0.510
				Seoul	2.199	***	0.526
				APT	1.085	***	0.470
				Home Owner	0.707	*	0.420
				Family	0.221	**	0.104
				University	0.284	*	0.170
				High Tech Perception	0.165	*	0.146
				Eco Perception	-0.497	***	0.175
				Utility Cost	0.660	***	0.153
				Commute	-0.012		0.080
				Home price>5	-0.621		0.541
LL	-1678.0		45.7				

*** Significance at the 1% levels, ** Significance at the 5% levels, * Significance at the 10% levels.

The pooled utility coefficient for each attribute indicated the same direction among all three models. Table 15 shows the empirical result of HVSC Logit model on zero energy house choice behavior. Respondents had a high level of utility for zero-energy houses built by large corporations (2.331). The utility of the respondents at the population level for the installation of renewable energy was found to be insignificant. In the case of ventilation facilities, the heat recovery type ventilation was shown a negative sign (-0.680). Respondents may think that increasing construction costs due to ventilation installation is unnecessary.

The longer the walking time to access major facilities (bus stops, schools, etc), the lower the utility of respondents (-1.442). For the reduction of carbon emissions, respondents derived positive utility (0.460). The result can be interpreted as an indication that respondents have a clear amount of money to reduce carbon emissions. Respondents showed a statistically significant positive utility for heat and electricity (utility) cost reduction (1.550). For the increase in costs, respondents derived a significant negative utility (-1.851). For no choice, respondents derived a negative coefficient (-3.314), which means that when respondents are given zero energy house alternatives, the probability of choosing a zero energy house alternative to an existing type of housing is high.

Table 16. Result of T-Test of Stated Attendance

	Group (1:Attendance)	Obs	Mean	Std. Err.	p-value (Ha: gr(1)-gr(0)<0)
Major Firm	0	520	-0.233	0.037	0.0000
	1	181	0.248	0.068	
	diff	-	-0.482	0.075	
Access Time	0	498	-0.097	0.042	0.0027
	1	203	0.120	0.067	
	diff	-	-0.218	0.078	
Renewable	0	494	-0.219	0.041	0.8596
	1	207	-0.297	0.057	
	diff	-	0.079	0.073	
Vent Type	0	366	-0.257	0.046	0.6696
	1	335	-0.284	0.042	

	diff	-	0.027	0.063	
CO2 Reduction	0	408	-0.171	0.043	0.3093
	1	293	-0.138	0.051	
	diff	-	-0.033	0.066	
Utility Cost Reduction	0	260	0.314	0.052	0.0006
	1	441	0.523	0.039	
	diff	-	-0.209	0.064	
Construction Cost	0	291	0.108	0.047	0.0000
	1	410	0.551	0.045	
	diff	-	-0.443	0.066	

For sensitivity check, as the questionnaire included stated attendance of respondents with five scale Likert questions about attendance in each variable. The five-level Likert scales were normalized into mean zero and variance 1. If the respondent had answered the same value to all questions, then the normalized value reduced into zero. The sample was divided into attendance group and non-attendance group. Then, t-test by each group was performed. The attributes that showed strong preference, which includes Major Firm, Access Time, Heat Cost Reduction and Construction Cost, turned out that normalized Likert scale has significantly larger when latently estimated attribute selection is selected. In other words, if respondents answered that he or she had strongly attended an attribute, then he or she attended the attribute, and it is captured latently.

Table 17. Summarized Marketing Metric of TBC

	Seoul	APT	Home Owner	Family	University	High Tech Perception	Eco Perception	Heat Cost	Commute	Home price>5
Major Firm	+	+	-			-		+	-	+
Renewable		+	-	+	+	-	+		-	-
Vent Type		-		-		+	-			
Access Time	-			+	-	-	+		+	
CO2 Reduction	+	+		-		+		+		-
Utility Cost Reduction	+		-	+		+	-		-	+
Cost	-	-	+	+			-	-		
No Choice	+	+	+	+	+	+	-	+		

The marketing metric for consumers derived from the results of HVS model is presented in Table 16. Residents in Seoul selected alternatives based on major firm, CO2 reduction, utility cost reduction, and no choice, and have a tendency that not considering accessibility and costs. It can be interpreted that the home price of Seoul is expensive and they are living in an environment with good access to public transportation and facilities.

For those currently residing in the apartment, they chose alternatives based on major firm, renewable energy, reduced carbon emissions, and no choice, and did not consider ventilation type and cost. Homeowners chose alternatives considering cost and no choice (status quo) and did not include major firm,

renewable in their decision-making process.

People with a large number of family members made decisions based on renewable, accessibility, utility cost savings, cost, and no choice, and did not consider ventilation or carbon emissions reduction in the process of choice. The higher the number of families, the more attention was paid to the living environment and cost elements of the house in which they live. For college graduates, there was a tendency to focus more on renewable energy and no choice alternative.

People with high-tech awareness opted for alternatives by concentrating on ventilation types, carbon emissions, energy savings, and no choice but with less consideration of builder size, renewable energy, and accessibility. In addition, people with a strong interest in the environment have considered access to renewable energy, public transport, and facilities. People currently with higher utility costs were more likely to choose alternatives that take into account brand, CO2 reduction, and no choice.

Those with long commute time tend to choose alternatives in terms of accessibility. Those who live in a house with more than 500 million KRW of house price or secured tend to choose alternatives considering apartment brand and heat cost reduction.

Table 18. Attribute Attendance/Non-Attendance Patterns in ZEH

Rank	Major Firm	Access Time	Renewable	Vent Type	CO_2 Reduction	Utility Cost Reduction	Cost	No Choice	Total
1	0	0	0	1	1	1	1	1	30
2	0	0	0	1	1	1	0	1	18
3	0	0	0	0	0	1	0	1	18
4	0	0	0	0	0	1	1	1	15
5	0	0	0	1	1	1	1	0	14
6	1	0	0	0	0	1	0	1	13
7	0	0	0	1	1	0	1	0	13
8	0	0	0	1	0	1	1	0	13
9	1	0	0	1	1	1	0	1	12
10	0	1	0	1	0	0	1	0	12
11	0	1	0	0	0	0	1	0	12
12	0	1	1	0	0	1	1	0	11
13	0	0	0	1	0	1	1	1	11
14	0	0	0	0	1	1	0	1	11
15	0	1	0	0	0	1	1	0	10
16	0	0	1	0	0	1	1	1	10
17	0	0	0	1	0	0	1	1	9
18	0	0	0	0	1	1	1	1	9
19	1	0	0	0	0	1	1	1	8
20	0	0	1	1	0	1	1	1	8
21	0	0	0	1	1	0	1	1	8
22	0	0	0	1	0	0	1	0	8
23	0	0	0	0	0	1	1	0	8
Else									420
Prob	25.8%	29.0%	29.5%	47.8%	41.8%	62.9%	58.5%	58.3%	

1: attendance, 0: non-attendance

Table 17 shows attribute non-attendance patterns in order of frequency. Because there are many attributes in alternatives, only those with more than eight observations were included. About 26% attended on the major firm attribute, 29% on accessibility, 30% on the renewable energy, 48% on ventilation, 42% on CO2 emission reduction, 62.9% on the reduction of utility expenses, 59% on the cost increment, and finally on no choice 58%. The result shows that the most important attributes for the zero-energy house was the reduction of utility expenses, saving energy consumption. Also, zero energy house attributes were mainly attended on making a decision such as ventilation type, implementation of renewable energy. In conclusion, for the successful implementation of zero energy supply plan, rather than putting all focus into the considerable attributes of house, the government and the construction firms should mainly focus on zero energy house attributes such as renewable, ventilation and energy efficiency and the cost increment due to improving energy efficiency.

It may be quite suspicious that the overall level of attendance ratio is lower than what researchers expected. However, most of ANA suggested that only small portion of individuals, about 3~5%, focused on all attributes and the level of attendance rate is quite acceptable compared to prior literature on A-NA (Lagarde, 2013; R. Scarpa et al., 2013; Riccardo Scarpa & Willis, 2009). Therefore, the estimated attendance rate is quite acceptable in same manner.

Comparing mixed logit relative importance measure, the HVSC selection ratio

shows similar results on relative importance in mixed logit model. Relative importance is calculated by multiplying the coefficients by range of attributes, different from relative importance, selection ratio actually captures individual attendance toward attributes, attendance rate from HVS model is more regularized importance measures.

Table 19. Comparison between Mixed Logit RI and HVSC Selection Ratio

	Cost Increase	Utility Cost Reduction	Access time	CO2 Reduction	Major Firm	Heat Exchange Vent	Mechanical Vent	Renewable
Mixed Logit RI	28.67%	19.90%	12.05%	10.89%	9.49%	9.09%	5.61%	4.32%
Mixed Logit RI Rank	1	2	3	4	5	6	7	8
HVSC Selection Ratio	58.49%	62.91%	28.96%	41.80%	25.82%	47.79%		29.53%
HVSC Selection Rank	2	1	6	4	7	3		5

Among all models (HVSC, HVS, HB), the suggested model shows the best performance on information criterions (WAIC 4277.09, LOO 4402.15), suggesting that the suggested model is appropriate in ZEH choice situation.

Table 20. Comparison of Information Criterion in HVS - WAIC (ZEH)

	WAIC	pWAIC	dWAIC	weight	SE
HVSC Logit	4277.09	746.5	0	0.67	78.91
HVS Logit	4343.16	878.92	66.07	0.33	74.85
HB (Covariate) Logit	4378.63	1031.45	101.54	0	82.10
HB (Mixed) Logit	4513.66	945.67	236.57	0	77.63

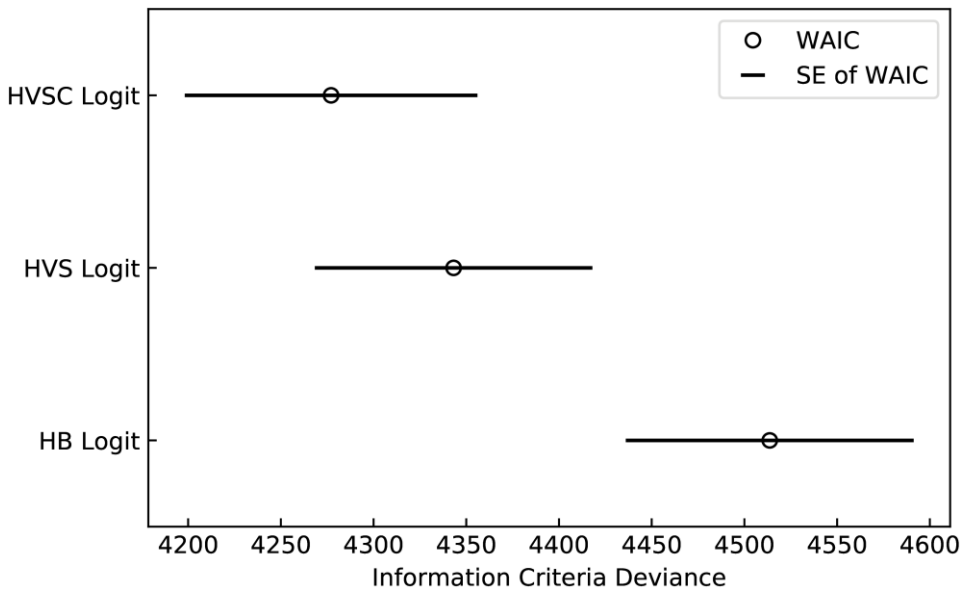


Figure 17. Comparison Diagram of Information Criterion in HVS – WAIC (ZEH)

Table 21. Comparison of Information Criterion in HVS - LOO (ZEH)

	LOO	pLOO	dLOO	weight	SE
HVSC Logit	4402.15	809.03	0	0.82	81.5
HVS Logit	4578.72	996.7	176.57	0.18	79.74
HB (Covariate) Logit	4683.98	1186.74	281.83	0	87.92
HB (Mixed) Logit	4736.77	1057.22	334.61	0	81.97

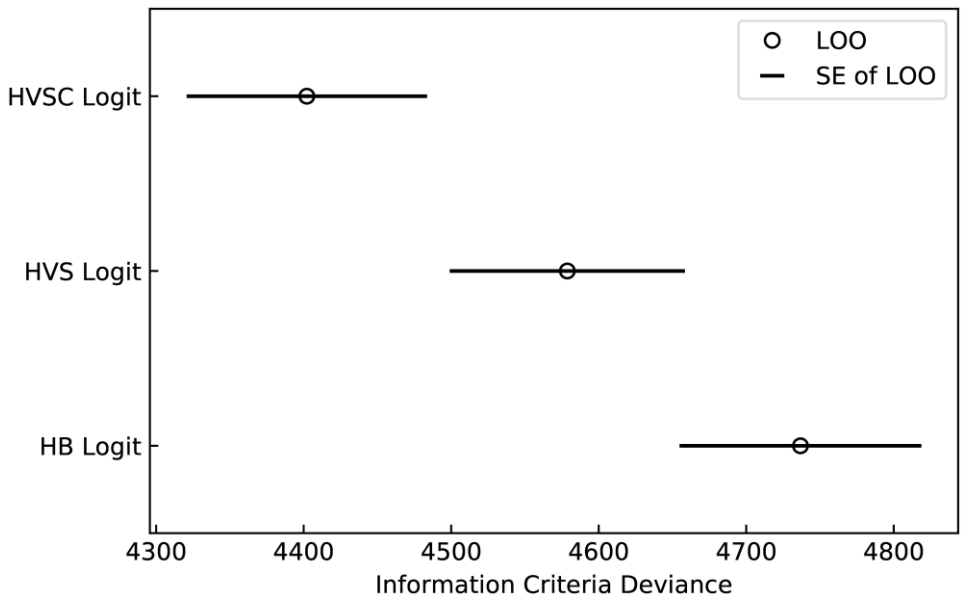


Figure 18. Comparison Diagram of Information Criterion in HVS – LOO (ZEH)

4.1.3.2 Heterogeneous Heuristic Decision-making Behavior of ZEH

This section reports empirical results of a heterogeneous choice model for respondent decision heuristics strategy on zero energy house choice situation. The result of HDH Cov. RUM-RRM Logit model is shown in Table 22. Full comparison of HDH Cov. RUM-RRM Logit, HDH RUM-RRM Logit, RUM model and RRM Logit model is included in Appendix 3. In all four models, sample level utility coefficients were in the same direction, except for non-significance utility coefficients. Log-likelihood of HDH RUM-RRM (-1571) showed slightly lower than HDH Cov. RUM-RRM (-1571). but two reference models' log-likelihood was far below those two (RUM: -1662, RRM: -1919). Except for the RRM part, the RUM part shows similar results to the previous model.

Table 22. Empirical Result of HDH behavior with Covariates in ZEH

Attributes	Mean		S.D.	Covariates	Mean		S.D.
(Dummy)							
Brand	0.511	***	0.153				
Renewable	-0.305	***	0.093				
Mechanical Vent	-0.240	**	0.162				
Heat Recovery Vent	-0.760	***	0.225				
No Choice	-1.262	***	0.332				
(RUM)				Seoul	-2.449	***	0.444
Access Time	-1.072	***	0.269	APT	0.043		0.415

(RRM)				Home Owner	0.316		0.391
Access Time	0.437	**	0.206	Family	0.032		0.203
				High tech Perception	-0.305	**	0.157
				Eco perception	0.471	*	0.250
				Commute	0.278	***	0.097
				Utility cost	-0.307	***	0.128
(RUM)				Seoul	-0.034		0.325
CO2 Reduction	-0.072		0.243	APT	-0.581		0.730
(RRM)				Home Owner	-0.396		0.648
CO2 Reduction	-0.263		0.269	Family	-0.195		0.294
				High tech Perception	0.221		0.233
				Eco perception	-0.342		0.399
				Commute	0.180		0.233
				Heat cost	-0.022		0.401
(RUM)				Seoul	0.441		0.404
Utility Cost Reduction	1.326	***	0.186	APT	0.006		0.256
(RRM)				Home Owner	0.228		0.269
Utility Cost Reduction	0.151		0.165	Family	0.703	***	0.276
				High tech Perception	0.258	*	0.141
				Eco perception	-0.092		0.220
				Commute	-0.063		0.310
				Utility cost	0.176		0.179
(RUM)				Seoul	1.343	***	0.253
Cost	-0.294	*	0.236	APT	0.812	***	0.156
(RRM)				Home Owner	0.060		0.279
Cost	-0.353		0.773	Family	-0.179		0.174
				High tech Perception	0.465	***	0.185
				Eco perception	-0.217	**	0.145
				Commute	-0.093		0.097
				Utility cost	0.301	**	0.144
Choicelogp	-1574	***	51.806				

bprecision	9.406	***	0.527

*** Significance at the 1% levels, ** Significance at the 5% levels, * Significance at the 10% levels.

For the regret minimization coefficient, only the attribute for the access time is significant in pooled sample level coefficients (0.437). To observe deterministic characteristics of consumer decision-making structure, significant positive coefficients of sociodemographic characteristics induce consumer decision-making structure as utility maximization, and significant negative coefficients induce consumer decision-making structure as regret minimization. For access time, for inhabitants in Seoul, the higher the high-tech perception, and the higher the heat cost expenditure, the higher the tendency for consumers to minimize regret. On the contrary, someone who has higher eco-perception and someone who has longer commuting time has utility maximization structure in access time. Those who have the larger family size and higher high tech perception has utility maximization structure in utility cost reduction. Inhabitants in Seoul, inhabitants in the apartment and someone who has higher high tech perception and someone who spends higher utility cost has utility maximization structure in cost increase. However, someone who has higher eco perception has regret minimization structure in cost. The result implies that those who care about the environment are those who can make modest compromises with the cost increase of the zero energy house.

Table 23. Combination of Heterogeneous Decision-Making Structure (ZEH)

Rank	Access Time	Reduce CO2	Utility Cost Reduction	Cost	Count
1	RRM	RRM	RUM	RUM	250
2	RUM	RRM	RUM	RUM	84
3	RRM	RRM	RRM	RUM	73
4	RUM	RRM	RRM	RRM	59
5	RUM	RRM	RRM	RUM	57
6	RUM	RRM	RUM	RRM	56
7	RRM	RUM	RUM	RUM	36
8	RRM	RUM	RRM	RUM	35
9	RRM	RRM	RUM	RRM	19
10	RRM	RRM	RRM	RRM	8
11	RRM	RUM	RRM	RRM	7
12	RUM	RUM	RRM	RUM	7
13	RUM	RUM	RRM	RRM	6
14	RRM	RUM	RUM	RRM	3
15	RUM	RUM	RUM	RUM	1
Total	270	95	449	543	701
RUM Ratio	38.5%	13.6%	64.1%	77.5%	
RRM Ratio	61.5%	86.4%	35.9%	22.5%	

The most visible pattern of the heterogeneous decision-making structure in ZEH choice situation is regret minimization in access time and reduction of carbon emission, and utility maximization in utility cost reduction and cost. Approximately 62% of respondents and 86% of respondents had regret minimization decision-making structure in access time and CO2 reduction,

respectively. 64% of respondents and 78% of respondents have utility maximization decision structure for utility cost reduction and cost increase, respectively.

In the model fit comparison, the HDH Cov. RUM-RRM model showed slightly better performance than the HDH RUM-RRM model in both WAIC and LOO. Both models performed much better than pure RUM (HB Logit) and pure RRM models. Thus, it can be seen that heterogeneous decision heuristics models are more appropriate than pure RUM model or pure RRM model, and it can be said that respondents have the mixed decision structure.

Table 24. Comparison of Information Criterion in HDH - WAIC (ZEH)

	WAIC	pWAIC	dWAIC	weight	SE	dSE
HDH Cov.RUM-RRM	4338.08	929.15	0	0.58	77.8	0
HDH RUM-RRM	4352.03	944.32	13.95	0.42	76.2	19.51
RRM	4525.32	945.35	187.24	0	77.46	21.7
RUM	4887.69	850.23	549.61	0	79.04	41.76

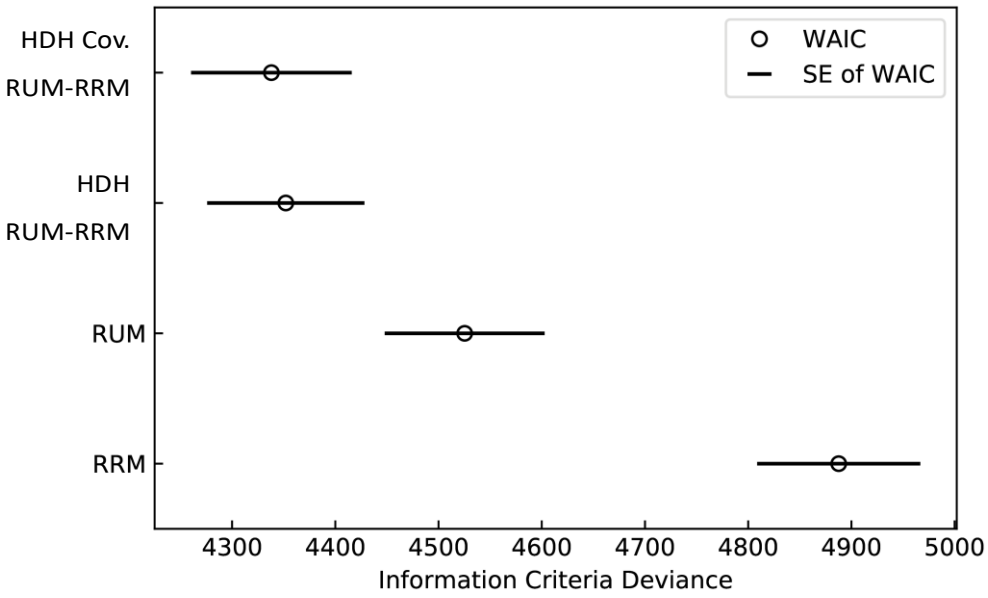


Figure 19. Comparison Diagram of Information Criterion in HDH – WAIC (ZEH)

Table 25. Comparison of Information Criterion in HDH - LOO (ZEH)

	LOO	pLOO	dLOO	weight	SE	dSE
HDH Cov. RUM-RRM	4575.81	1048.02	0	0.65	82.62	0
HDH RUM-RRM	4614.22	1075.42	38.41	0.35	81.91	23.55
RRM	4748.82	1057.1	173.01	0	81.93	24.38
RUM	5039.72	926.25	463.9	0	82.34	44.1

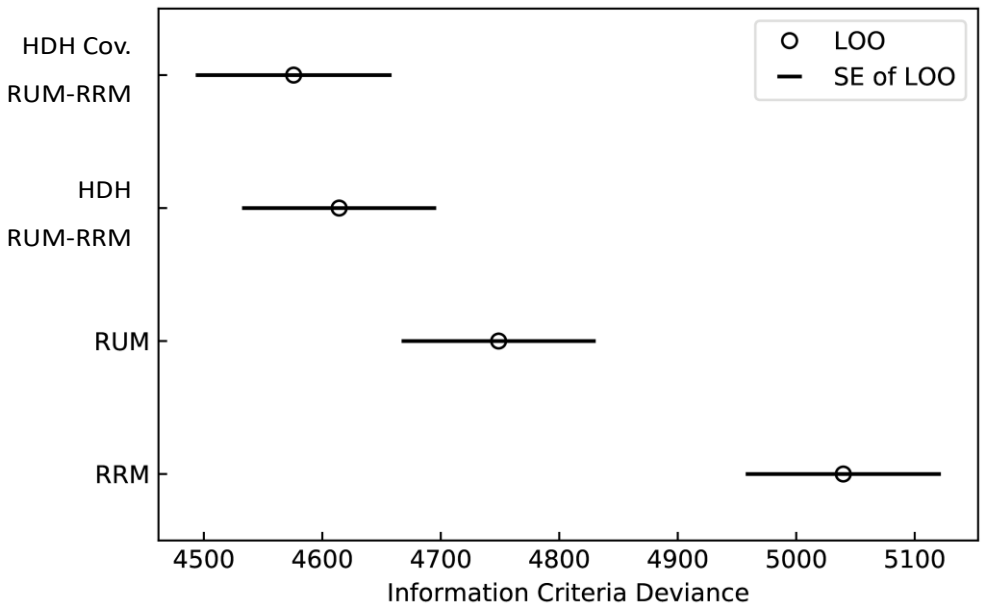


Figure 20. Comparison Diagram of Information Criterion in HDH – LOO (ZEH)

4.1.4 Discussions

This section empirically analyzed the heterogeneous decision-making structure of consumers through zero energy house choice behavior. Among the HVSC Logit, HVS Logit and HB Logit models, the HVSC model showed the best estimation fit. Empirically, HVSC Logit is considered well behaved. Among the four HDH Cov RUM-RRM, HDH RUM-RRM, RUM, and RRM models, the HDH Cov RUM-RRM model showed marginally better estimation fit among the four models.

Table 26. Comparison of Information Criterion of all models (ZEH)

	WAIC	pWAIC	LOO	pLOO	LL
HVSC Logit	4277.09	746.50	4402.15	809.03	-1677.99
HVS Logit	4343.16	878.92	4578.72	996.70	-1613.20
HB (Covariates) Logit	4378.63	1031.45	4683.98	1186.74	-1522.23
HB (Mixed) Logit (RUM)	4513.66	945.67	4736.77	1057.22	-1655.28
HDH Cov. RUM-RRM	4338.08	929.15	4575.81	1048.02	-1574.87
HDH RUM-RRM	4352.03	944.32	4614.22	1075.42	-1570.71
RRM	4525.32	945.35	4748.82	1057.1	-1918.81

Since the two proposed models have different structural formation, one model captures attribute non-attendance behavior and the other model captures

heterogeneous decision-making structure among RUM and RRM, the two models are incomparable. But if all models are considered at once, the HVSC Logit model showed the best model fit for telecommunication bundling choice. The fact suggests that the HVSC model is a suitable model for explaining the zero-energy house choice behavior of consumers.

This can be explained by the complexity of the HDH Cov. RUM-RRM model. In the case of the model complexity, there is a penalty for the complexity of the model, p-WAIC, and p-LOO. In HDH Cov. RUM-RRM model, p-WAIC and p-LOO are about 200 higher than the HVSC Logit model. (Table 26)

4.2 The Study on Consumer Choice Behaviors in High-Tech Goods 2 – Telecommunication Bundling Choice (TBC)

This section reports the empirical results of the suggested models in the telecommunication bundling choice. The suggested two models and baseline reference models are estimated, and the results are reported in Appendix 3. This section discusses the empirical results of suggested models and information criterion of the models

4.2.1 Introduction

In recent years, bundling has become a common marketing technique. When selling a variety of items, bundling became a pervasive marketing technique because of the claim that bundling of complementary products increases the profit of the company (Leszczyc & Häubl, 2010). In sellers' perspective, offers for each good simultaneously could incur substantial transaction costs, shipping and handling costs. Also, in the buyers' perspective, they confront search costs to find out what they want. One way for sellers to reduce such costs is to use bundling marketing. They offer multiple products as a packaged good for single bidding. Those strategic approach entails economies of aggregation (Bakos & Brynjolfsson, 2000) and incur additional revenue that might be obtained by selling products

individually. Several fields reported that bundling of complementary products enhance sales of corporation, foods (Agarwal & Chatterjee, 2003), online bidding such as e-Bay, (Leszczyc & Häubl, 2010), service plan and mobile device (Yang & Ng, 2010), clothing (Janiszewski & Cunha, 2004) ,and packaged goods (Foubert & Gijsbrechts, 2007).

Each previous literature about bundling suggests different implication. Among the literature, Janiszewski and Cunha (2004) suggested that the asymmetric perceived values on discount bundling compositions, a product in the bundle can provide more or less appealing value (utility) than an equivalent discount to another product. This is because people weights asymmetrically based on what they have evaluated and their heterogeneous decision-making structure. One explanation for such asymmetry is the anchoring effect (reference-dependent) and another explanation is different value function. (Mazumdar & Jun, 1993; M. S. Yadav, 1995; Manjit S. Yadav, 1994)

In the case of telecommunication plans, which commonly provided several complementary network plans concurrently (such as mobile, broadcasting (Pay-TV), wired telephone (Fixed telephone and VoIP) and wired internet) by integrated network operators, the bundling marketing is common in this area. Klein and Jakopin (2014) estimated that the user's perception of the utility of mobile service bundle within the telecommunication service bundle in the German case, bundling internet access, voice call minutes, text messaging services. They

suggested that current form of bundling strategies by the main players in German mobile industry is reasonable. Pereira, Ribeiro and Vareda (2013) suggested that the case of triple-play, bundling with fixed telephone, fixed broadband and subscription of pay television are meaningful measures in the telecommunication market in Portuguese. Srinuan, Srinuan, and Bohlin (2014) suggested that discount, service providers (brands), education, income level, and residential area are major determinants for selecting multiple service adoption in a double-play, triple-play and quadruple-play telecommunication bundling market in Swedish. Unlike general research, a study suggested that consumer prefers simply send a bill in one bundle without discounts in Turkish market (Mithat Üner, Güven, & Tamer Cavusgil, 2015). They suggested that the Turkish market of telecommunication was not yet matured and the bundling plans were not yet diffused much, meaning that perceptions toward discounts were low level.

In Korea, there are several bundling plans that telecommunication users can join among four telecommunication services (Kang, Jeong, & Kwon, 2014), Mobile, Internet, Broadcasting, VoIP (internet phone) and Fixed phone: double-play bundles (DPB; Broadcasting- Internet, Broadcasting-VoIP), triple-play bundles (TPB; Broadcasting-Internet-Fixed Phone, Broadcasting-Internet-VoIP, Broadcasting-Internet-Mobile), quadruple-play bundle (QPB; Mobile-Internet-IPTV-VoIP) and quintuple-play bundle (QPB (5); Broadcasting-Internet-Fixed Phone-VoIP-Mobile). Among this, majority household uses triple play bundles

including broadcasting services.

Table 27. Share of Bundle (2014.03, KISDI, re-formation) [3]

	(2014. 03.)	SO		IPTV		Total	2013. 09.	2013. 12.	2014. 03.
	Combination	Subscribers	Share	Subscribers	Share	Subscribers	Subscribers	Subscribers	Subscribers
DPB	B+I	1,363,918	45.60%	1,628,158	54.40%	2,992,076	2,793,303	2,882,606	2,992,076
	B+V	299,080	100%	-	0.00%	299,080	297,371	297,114	299,080
TPB	B+I+F	40	0%	1,028,449	100%	1,028,489	973,092	1,001,885	1,028,489
	B+I+V	897,119	40.60%	1,311,652	59.40%	2,208,771	2,219,627	2,208,557	2,208,771
	B+I+M	3,654	0.20%	1,512,966	99.80%	1,516,620	1,046,122	1,267,233	1,516,620
QPB	B+I+F+V	-	0%	387,783	100.00%	387,783	392,892	397,279	387,783
	B+I+F+M	-	0%	825,944	100.00%	825,944	692,910	759,233	825,944
	B+I+V+M	13,527	2.80%	475,622	97.20%	489,149	386,533	444,291	489,149
QPB(5)	B+I+F+V+M	-	0%	340,315	100.00%	340,315	349,443	350,252	340,315
	Bundle with M	17,181	0.50%	3,154,847	99.50%	3,172,028			
	Total	2,577,338	22.10%	9,084,738	77.90%	11,662,076	9,151,293	9,608,450	10,088,227

B: Broadcasting, I: Internet, F: Fixed Telephone, V: VoIP, M: Mobile

This chapter analyzes heterogeneous consumer decision-making behaviors in selecting service plans bundling from system providers, mobile and broadcasting service plans. Previous literature suggests several implications about bundling in telecommunication industry but did not explore bundle choice tendency toward the discount. Therefore, this section analyzes bundle choice behavior among various discount combination.

[3] Kang, J., Jeong, H., & Kwon, Y. (2014). *A study on Improving Regulations for Bundles of Communications Services.*, KISDI Research Report 14-17

4.2.2 Data Descriptions

For empirical analysis, this dissertation collected data from the hypothesized conjoint survey. The survey was performed in November and December 2017, via face-to-face interviews by Gallup Korea. A total of 1508 people participated in the survey, who reside in Seoul and the metropolitan area and five major cities (Busan, Incheon, Daegu, Daejeon, and Gwangju). The interviewees were chosen through probability sampling with a quota to have representative demographic characteristics.

The survey was processed as follow. First, interviewees were asked about whether they use telecommunication services or not. If interviewees had answered no, then the survey ended. If yes, the interviewer explained the details of the questionnaires, the questions about socio-demographic characteristics and details of attributes in the conjoint survey and the choice situations suggested in the questionnaires. The descriptive statistics of socio-demographic characteristics of survey respondents are shown in Table 28 and attributes in conjoint surveys are listed in Table 29.

The age of survey participants ranged from 20 to 59 years, considering the understanding of the broadcasting and telecommunication plans and whether respondents can make a decision on a subscription plan or not. The sample

includes more than half actual decision-makers about telecommunication service subscription (67.51%), and 35.54% of respondents are bundling mobile service and broadcasting services. Also, of the respondents, 24.2% responded they have not change the broadcasting service for six years, and a majority (59.62%) responded they changed once every six years. 16.18% of the respondents responded that they changed the broadcasting service more than two times among six years, and only few responded that they changed service more than three times. Since the contract period of Korea's broadcasting communication service is usually three years, it is difficult to change more than three times in six years. Bundling with mobile subscription often includes the mobile plans of all family members. The more the number of family members, the more complicated it becomes to bundle, so the number of family members is included as a control variable. (Table 28)

Table 28. Socio-Demographic Characteristics of the TBC Survey Respondents

Category	Group	Freq.	Percent
Residential district	Seoul	425	28.18
	Other area	1083	71.87
Gender	Male	764	50.66
	Female	744	49.34
SO change frequency within 6 years	0	365	24.2
	1	899	59.62
	2 ~	244	16.18
Education	High school	616	40.85
	College	326	21.62
	University & Grad	559	37.53
Household expense (Unit: Million Won)	~ 2	212	14.06
	2 ~ 3	608	40.32
	3 ~ 4	435	28.85
	4 ~ 5	178	11.8
	5 ~	75	4.97
Current bundling with mobile & pay-TV	Not Bundled	972	64.46
	Bundled	536	35.54
Actual household decision-maker	Non Decision Maker	490	32.49
	Decision Maker	1,018	67.51
Number of family	1 & 2	226	14.99
	3 & 4	1197	79.37
	Above 4	85	5.64
Monthly Phone bill (Unit: Thousand Won)	~ 4	191	12.67
	4 ~ 5	264	17.51
	5 ~ 6	464	30.77
	6 ~ 7	361	23.94
	7 ~	228	15.12
	Total	1,508	100

Table 29. Details of Attributes in TBC Conjoint Survey

Attributes	Description	Level
Mobile Carrier	system operator that provides mobile services and broadcasting services	SKT (baseline) KT LGU+
Period	the stipulated time that consumer mandatorily using bundled telecommunication services	1yr 2yr 3yr
Discount Mobile	Discount from Mobile telecommunication service in a bundled plan	10% 50% 90%
Discount Pay-TV	Discount from broadcasting subscription service in a bundled plan	10% 50% 90%

The attributes in the conjoint questionnaires are as follows: Mobile Carrier, Period, Discount Mobile, Discount Pay-TV. The mobile carrier is a company that provides mobile services and broadcasting communication service at once with bundling plans. SKT, KT, and LGU+ are the major network providers that provide bundled services. Since the use of bundling services should be tied to a mandatory contract for a certain period, the mandatory contract period is included as period, which is a year, two year, and three year as period attribute level as in a real-world situation. The bundled service offers different discount rates for each mobile and pay-TV service. Both discount rate is independently having three-level attributes, 10%, 50%, and 90% (Table 29).

4.2.3 Empirical Results

This section reports the analysis results about consumer SO bundling choice behavior via suggested two models, heterogeneous variable selection behavior of bundling choice with respondents socio-demographic characteristics (ANA behavior) and exploring heterogeneous decision-making strategy with respondents socio-demographic characteristics. Section 4.2.3.1 reports heterogeneous variable selection behavior and section 4.2.3.2 reports heterogeneous decision-making strategy behavior.

4.2.3.1 Heterogeneous Variable Selection behavior of TBC

This section reports heterogeneous variable selection behavior on telecommunication bundling choice situation. The result of the HVSC Logit is shown in Table 14. Full comparison of HB Logit and HVS Logit is included in Appendix 3. In all three models, sample level utility coefficients were in the same direction, except for non-significance utility coefficients. Log-likelihood of HVSC Logit (-2891.1) showed the lowest level among the three models (HVS Logit: -2897.1, HB Logit: -3101.0), suggesting that the HVSC Logit had the best performance among reference models.

The pooled utility coefficient for each attribute indicated the same direction for all three models. Table 30 shows the empirical result of HVSC Logit model on telecommunication bundling choice behavior. The baseline of the mobile carrier was SKT, and the relative utility of KT and LGU+ was estimated. The coefficients for KT and LGU+ all showed significant positive signs. Consumers relatively preferred KT and LGU+ compare to SKT and preferred KT most. Respondents had a significant negative utility as the duration increases (-0.425). The longer the subscription period, the more likely consumers are tied to the company and the less likely they will benefit from other promotions. Mobile subscription service discount and paid broadcasting service discount both had significant positive utility coefficients.

Table 30. Empirical Result of HVS Behavior with Covariates on TBC

	Mean		S.D.		Mean		S.D.
(Mobile Carrier)				Constant	-0.336		0.664
KT	1.312	**	0.578	Age	-0.194		0.168
LGU+	1.025	**	0.454	Male	0.005		0.272
				Decision	-1.074	***	0.485
				Bundle Mobile	0.946	***	0.335
				Installment Payment	-0.002		0.578
				Phone bill	0.177		0.176
				Income	-0.050		0.148
				Edu	-0.223		0.175
				Change w/i 6yr	0.747	**	0.433
Period	-0.425	***	0.108	Constant	-0.797		0.887
				Age	0.236		0.210
				Male	0.083		0.377
				Decision	0.563		0.644
				Bundle Mobile	0.145		0.435
				Installment Payment	0.104		0.524
				Phone bill	-0.341		0.240
				Income	0.398	**	0.209
				Edu	0.142		0.274
				Change w/i 6yr	1.262	***	0.455
Discount Mobile	0.984	***	0.186	Constant	1.007	**	0.521
				Age	0.185		0.179
				Male	-0.032		0.377
				Decision	-0.772	*	0.432
				Bundle Mobile	0.026		0.428
				Installment Payment	0.617	*	0.412
				Phone bill	-0.099		0.208
				Income	-0.190		0.159
				Edu	0.087		0.164

				Change w/i 6yr	0.137		0.309
Discount Pay-TV	1.681	***	0.187	Constant	-0.915	**	0.371
				Age	-0.103		0.133
				Male	-0.281		0.275
				Decision	0.271		0.327
				Bundle Mobile	0.501	**	0.259
				Installment Payment	0.956	***	0.356
				Phone bill	-0.088		0.164
				Income	0.172		0.137
				Edu	-0.386	***	0.153
				Change w/i 6yr	1.042	***	0.275
Choicelogp	-2891.13		94.16				

*** Significance at the 1% levels, ** Significance at the 5% levels, * Significance at the 10% levels.

In terms of variable selection, above all, age, gender and telecommunication rate did not have a significant effect on the choice of variables. The actual decision-makers tended not to consider the mobile carrier (-1.074) and consumers who already use the bundled product of mobile telecommunication service and broadcasting communication service considered mobile carrier for decision making. It has been found that the actual decision-makers for subscription to telecommunication services tend to consider the choice by excluding the mobile carrier (-1.074) and the mobile service discount variable (-0.772). Users who have already used the combination of broadcasting service and mobile service considered mobile carrier (0.946) and the discount rate of broadcasting service (0.501) to be included in decision making. Consumers who use installment

payments for telecommunication products were found to make decisions by including both mobile discount (discount mobile: 0.617, discount pay-TV: 0.956). Those with a high-income level made a decision based on the period (0.398), but the results were not significant for the remaining variables. The higher the education level, the more likely it was for the discount not to be included in the decision (-0.386). Consumers who have a history of changing their subscription to broadcasting service even once within six years can make decisions based on all variables except for mobile discount variables (each 0.747, 1.262, 1.042). Therefore, the suggesting marketing metric of telecommunication bundling choice is shown in Table 31.

Table 31. Summarized Marketing Metric of TBC

	Mobile Carrier	Period	Discount Mobile	Discount Pay-TV
Age				
Male				
Decision	-		-	
Bundle Mobile	+			+
Installment Payment			+	+
Phone bill				
Income		+		
Edu				-
Change w/i 6yr	+		+	+

Those who are currently using the bundled service of broadcasting and mobile

and those who have changed the communication service for 6 years included the mobile carrier in the decision. The higher the income, the more likely the period will be included in the decision making. Those who are paying mobile phone installment and those who have a history of changing communication service within 6 years tend to include mobile discounts in their decisions. Those who are using mobile and broadcast bundled products, who are paying for mobile phone charges on installments and those who have a history of changing communications services within six years tend to consider cable discounts.

Table 32. Attribute Attendance/Non-Attendance Patterns in TBC

Rank	Mobile Carrier	Period	Discount Mobile	Discount Pay-TV	Total
1	0	1	1	1	481
2	1	1	1	1	454
3	0	1	1	0	123
4	1	0	1	1	107
5	0	0	1	1	94
6	0	0	1	0	90
7	1	1	1	0	52
8	1	0	1	0	29
9	0	1	0	1	20
10	1	1	0	1	19
11	0	1	0	0	17
12	0	0	0	0	7
13	1	0	0	1	6
14	0	0	0	1	6
15	1	0	0	0	2

16	1	1	0	0	1
Total	670	1167	1430	1187	1508
Ratio	44%	77%	95%	79%	100%

1: Attended, 0: Non-attended

In terms of sample-level patterns of attribute attendance/non-attendance behavior, a total of 16 patterns of attribute attendance/non-attendance is drawn from the HVSC Logit model, shown in Table 32. The above table is acquired that if selection probability is above .5, then inferred an individual attended on the variable. Four hundred eighty-one individuals focused on period, mobile service discount, and discount from broadcasting services and exclude mobile carrier. Four hundred fifty-four individuals attended on all the presented attributes. The ratio of attending mobile carrier attribute is 44%, the subscription period is 77%, mobile service discount 95% and broadcasting service discount 79%. The result implied that most of the people attended on mobile service discount and the majority of people attended on period and discount on broadcasting service.

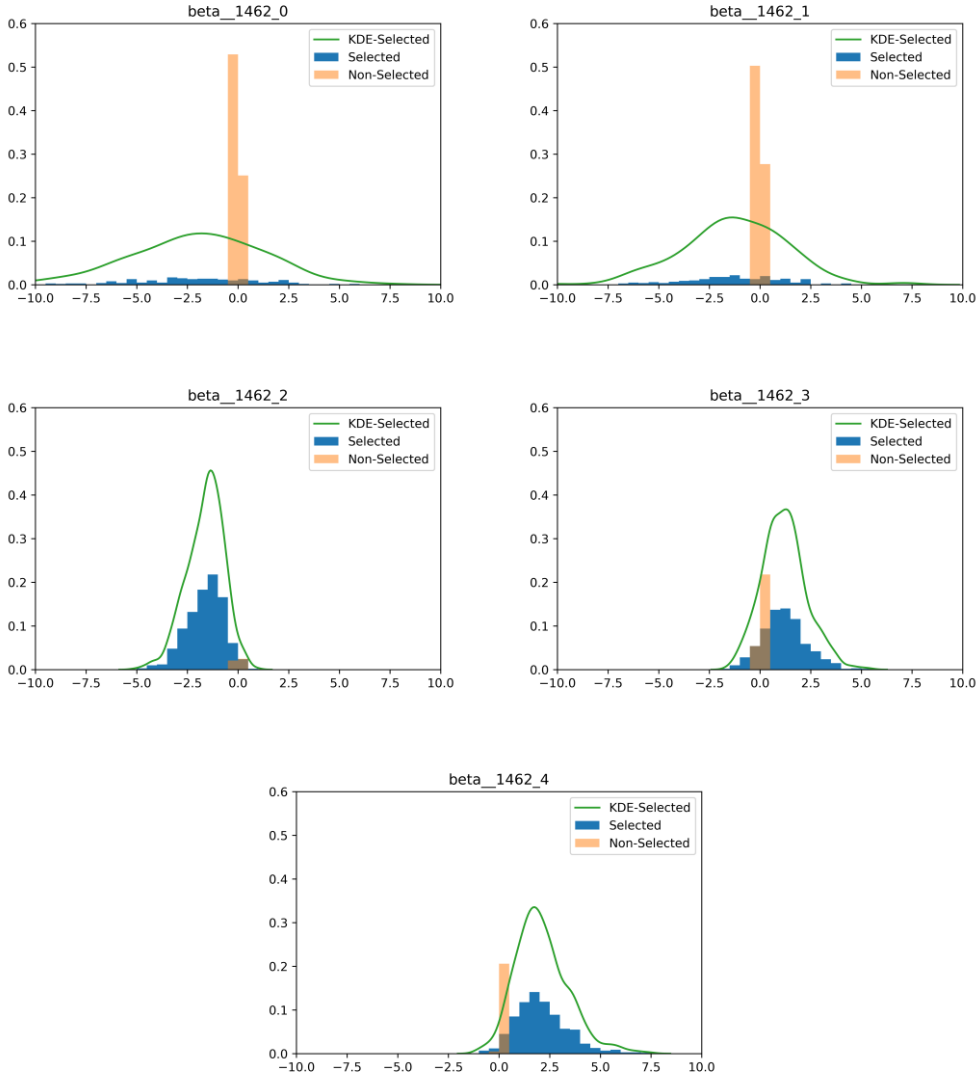


Figure 21. Histogram and KDE Plot of an Individual

For a simple illustration, for example, of one sample in rank one (individual 1462), selection of *(Mobile Carrier, Period, Discount Mobile, Discount Pay-TV) = (0,1,1,1)*, a density plot and a kernel density estimate of utility coefficients are

shown in Figure. 16. Probabilities of attendance on variables are *(Mobile Carrier, Period, Discount Mobile, Discount Pay-TV) = (0.220, 0.954, 0.728, 0.789)*.

The density of individual 1462 have very sharp near zero distributions on mobile carrier (KT, *beta_1462_0* and LGU+, *beta_1462_1*), and have the formal normal distributions for remaining variables (*beta_1462_2*, period; *beta_1462_3*, discount from mobile service; *beta_1462_4*, discount from broadcasting distribution). The density rising near zero in (*beta_1462_2*, *beta_1462_3*, *beta_1462_4*) is portion of residual of variable attendance probability (*0.046, 0.272, 0.211*).

In order to test the model fitness, WAIC comparison (Table 33, Figure 22) and LOO comparison (Table 34 Figure 23) for each reference models (HB Logit and HVS Logit) are showed. The comparison of WAIC and LOO all suggested that the HVSC Logit model has the goodness of fit above all reference models.

Table 33. Comparison of Information Criterion in HVS - WAIC (TBC)

	WAIC	pWAIC	dWAIC	Akaike weight	SE
HVSC Logit	8044.35	1752.28	0	0.95	84.33
HVS Logit	8136.32	1812.77	91.97	0.05	85.04
HB (Covariate) Logit	8488.69	1971.26	444.34	0	90.01
HB (Mixed) Logit	8699.59	1925.17	655.24	0	92.04

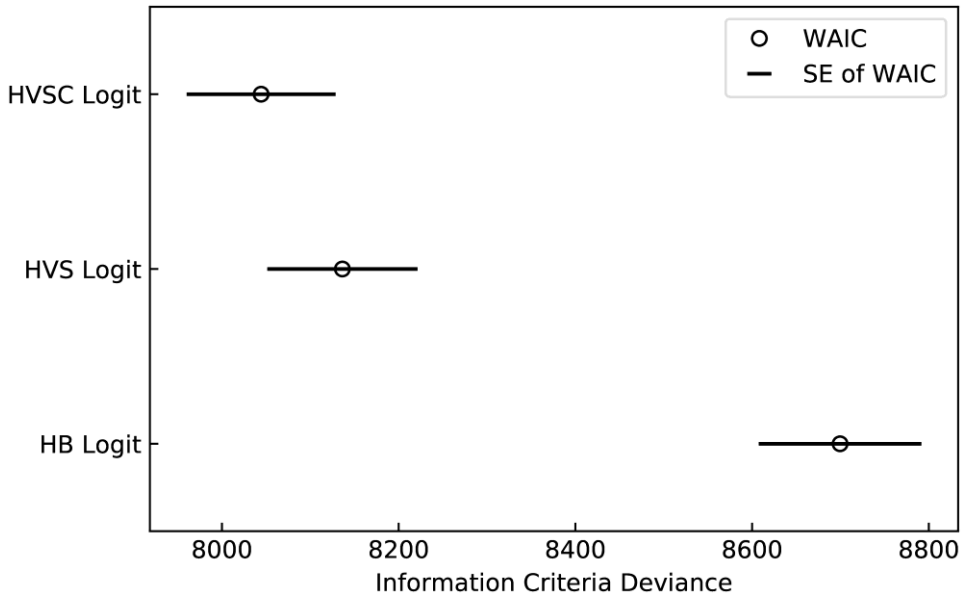


Figure 22. Comparison Diagram of Information Criterion in HVS – WAIC (TBC)

Table 34. Comparison of Information Criterion in HVS - LOO (TBC)

	LOO	pLOO	dLOO	Akaike weight	SE
HVSC Logit	8713.83	2087.02	0	0.76	92.48
HVS Logit	8799.87	2144.54	86.03	0.24	92.92
HB (Covariate) Logit	9207.29	2330.56	493.46	0	97.90
HB (Mixed) Logit	9313.59	2232.17	599.76	0	98.91

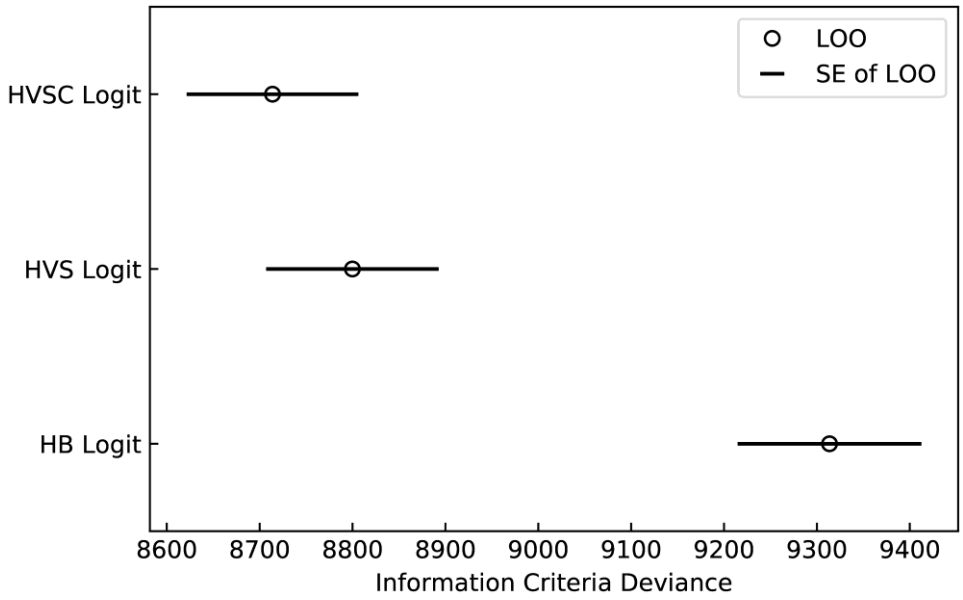


Figure 23. Comparison Diagram of Information Criterion in HVS – LOO (TBC)

4.2.3.2 Heterogeneous heuristic decision-making behavior of TBC

This section reports empirical results of a heterogeneous choice model for respondent decision heuristics strategy on telecommunication bundling choice situation. The result of HDH Cov. RUM-RRM Logit model is shown in Table 35. Full comparison of HDH Cov. RUM-RRM Logit, HDH RUM-RRM Logit, RUM model and RRM Logit model is included in Appendix 3. In all four models, sample level utility coefficients were in the same direction, excepts for non-significance utility coefficients. Log-likelihood of HDH Cov. RUM-RRM (-2874.9) showed the lowest level among four models (HDH RUM-RRM: -2941.4, RUM: -3110.6, RRM: -3457.4), suggesting that HDH Cov. RUM-RRM had the best performance among reference models.

Table 35. Empirical Result of HDH behavior with Covariates in TBC

	Mean		S.D.		Mean	S.D.
(Dummy)						
KT	0.479	*	0.297			
LGU+	0.151		0.225			
(RUM)				(Period)		
Period	-0.528	***	0.165	Decision	-0.287	0.298
(RRM)				Bundle-Mob	0.278	0.346
Period	-0.223		0.254	Phone Bill	-0.220	0.181
				Income	0.236	0.265

				Edu	0.236		0.258
				Change w/i 6yr	0.980	***	0.460
(RUM)				(Discount Mobile)			
Discount Mobile	1.995	***	0.372	Decision	-1.397	***	0.390
(RRM)				Bundle-Mob	-0.290		0.316
Discount Mobile	-0.102		0.187	Phone Bill	0.323	*	0.177
				Income	-0.170		0.182
				Edu	0.040		0.175
				Change w/i 6yr	0.209		0.237
(RUM)				(Discount Pay-TV)			
Discount Pay-TV	1.376	***	0.160	Decision	0.414	*	0.278
(RRM)				Bundle-Mob	0.459	*	0.295
Discount Pay-TV	0.559	**	0.278	Phone Bill	0.112		0.186
				Income	0.110		0.107
				Edu	0.031		0.201
				Change w/i 6yr	1.414	***	0.279
Choicelogp	-2874.9		101.9				

*** Significance at the 1% levels, ** Significance at the 5% levels, * Significance at the 10% levels.

In the Pooled parameters, except for the RRM part, the RUM part shows similar results to the previous model. Regret minimization coefficients for mobile service shows the insignificant result, and regret minimization coefficient for broadcasting subscription service was significantly positive.

Respondents with a history of changing their broadcast services within 6 years tend to make decisions about the period over utility maximization. Household decision makers about communication service tend to have regret minimization decision structures for mobile service discounts. Household decision makers,

users with combined mobile products and those who have changed their broadcasting service within 6 years tend to have utility maximization decision-making structure about discounts on broadcasting services.

Table 36. Decision Heuristic Patterns between RUM-RRM (TBC)

Rank	Period	Discount Mobile	Discount Pay-TV	Total
1	RUM	RRM	RUM	963
2	RUM	RUM	RUM	246
3	RRM	RRM	RUM	166
4	RRM	RRM	RRM	61
5	RUM	RRM	RRM	32
6	RRM	RUM	RUM	21
7	RUM	RUM	RRM	15
8	RRM	RUM	RRM	4
Total	1256	286	1396	1508
RUM Ratio	83.3%	19.0%	92.6%	
RRM Ratio	16.7%	81.0%	7.4%	

Above all, the major structural heterogeneous pattern in TBC sample is utility maximization in period and broadcasting subscription discount and regret minimization in mobile fee discount. Following from rank one pattern, utility maximization of all attributes showed the second most frequency patterns. For period and broadcasting subscription discount, each 83.3% and 92.6% of respondents has utility maximization structure. However, in mobile discount attribute, 81.0% of an individual judge via regret minimization.

The comparison of information criterion showed that HDH Cov RUM-RRM model has slightly better performance than HDH RUM-RRM model and way better performance than pure RUM and RRM models. The reason why the HDH Cov. RUM-RRM and HDH RUM-RRM performances are not significantly different is presumably because it did not include variables that could be sufficient explanation for the heterogeneous decision-making structure of respondents.

Table 37. Comparison of Information Criterion in HDH - WAIC (TBC)

	WAIC	pWAIC	dWAIC	weight	SE	dSE
HDH Cov. RUM-RRM	8354.61	1888.91	0	0.54	89.66	0
HDH RUM-RRM	8359.36	1901.23	4.75	0.46	88.56	17.09
RUM	8689.06	1906.93	334.44	0	91.77	20.42
RRM	9115.37	1721.36	760.75	0	88.55	36.92

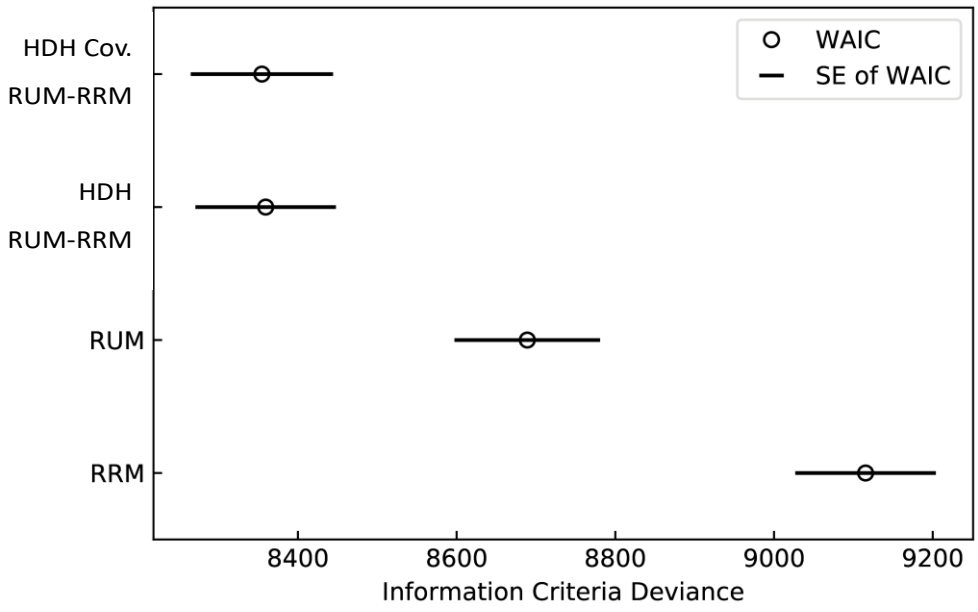


Figure 24. Comparison Diagram of Information Criterion in HDH - WAIC (TBC)

Table 38. Comparison of Information Criterion in HDH - LOO (TBC)

	LOO	pLOO	dLOO	weight	SE	dSE
HDH RUM-RRM	9022.63	2232.86	0	0.54	96.13	0
HDH Cov. RUM-RRM	9036.5	2229.85	13.87	0.46	97.8	23.78
RUM	9278.57	2201.68	255.94	0	97.75	20.74
RRM	9607.72	1967.53	585.09	0	94.04	38

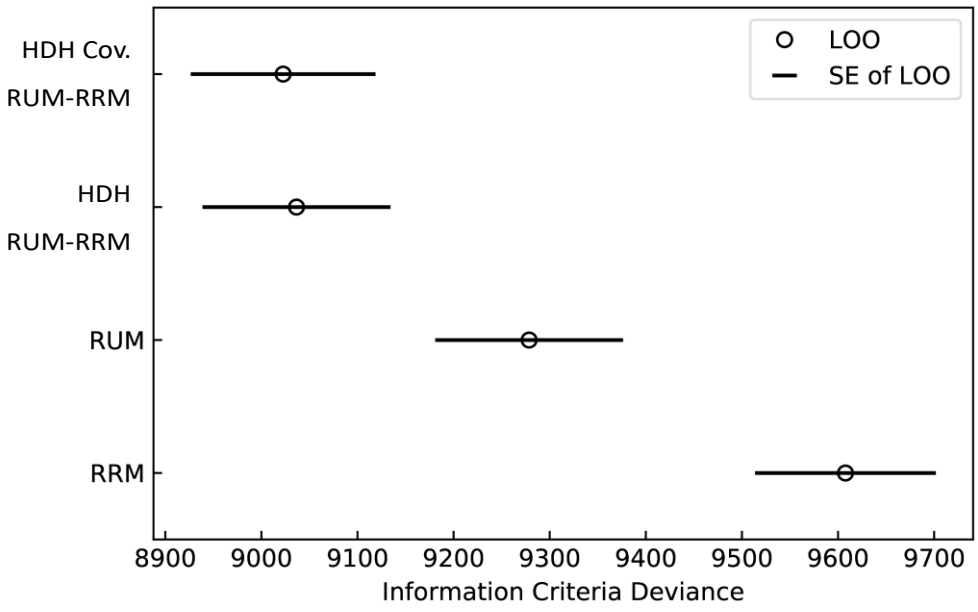


Figure 25. Comparison Diagram of Information Criterion in HDH – LOO (TBC)

4.2.4 Discussions

In this section, I empirically analyzed various heterogeneous utility structures for TBC of consumers. Among the HVSC Logit, HVS Logit and HB Logit models, the HVSC model showed the best estimation fit. Empirically, HVSC Logit is considered well behaved. Among the four HDH Cov. RUM-RRM, HDH RUM-RRM, RUM, and RRM models, the HDH Cov. RUM-RRM model showed marginally better estimation fit among four models.

Table 39. Comparison of Information Criterion of all models (TBC)

	WAIC	pWAIC	LOO	pLOO	LL
HVSC Logit	8044.35	1752.28	8713.83	2087.02	-2891.13
HVS Logit	8136.32	1812.77	8799.87	2144.54	-2897.67
HB (Mixed) Logit (RUM)	8699.59	1925.17	9313.59	2232.17	-3101.04
HB (Covariates) Logit	8488.69	1971.26	9207.29	2330.56	-2947.86
HDH Cov. RUM-RRM	8354.61	1888.91	9036.5	2229.85	-2874.88
HDH RUM-RRM	8359.36	1901.23	9022.63	2232.86	-2941.44
RRM	9115.37	1721.36	9607.72	1967.53	-3457.39

Since the two proposed models have different structural formation, one model is capturing attribute non-attendance behavior and the other model is capturing

heterogeneous decision-making structure among RUM and RRM, the two models are incomparable. However, if considering all models at once, like zero energy house choice situation, the HVSC Logit model showed the best model fit for telecommunication bundling choice. The fact suggests that the HVSC model is a suitable model for explaining the bundle selection behavior of consumers.

4.3 The Study on Consumer Choice Behaviors in High-Tech Goods 3 –Vehicle Choice (VC)

This section presents the differences between the HB Logit with Covariates model and the HVSC model with an empirical result. The results of the empirical case show that the estimated fitness of the model may be different depending on the characteristics of the empirical analysis data, and the result suggested that the model should be selected according to the characteristics of the data.

4.3.1 Introduction

After the Paris Agreement, each country is setting up a roadmap for diffusion electricity vehicles (EVs) to cope with carbon emissions. As mentioned in section 4.1.1, Korea is sixth-highest GHG emitting country in OECD and worlds' twelveth-highest GHG emitting country. Since Korea is the country with the highest carbon emissions, Korea government has been implementing policies for the diffusion of EVs and Hybrid Electricity Vehicles (HEVs) and the construction of EV charging infrastructure for the diffusion of environmentally friendly vehicles. At the same time, Korea government try to implement policies to spread new technology environment-friendly cars such as hydrogen fuel cell vehicles

(HFCVs). In addition to this, various policies are being implemented to curb carbon emissions in the transport sector through policies such as the early exit policy of old vans and subsidies for old diesel vehicles installing DPF.

The most significant advantage of EVs compared to other forms of internal combustion engine vehicles such as gasoline or diesel-fueled vehicles is that it is relatively easy to control carbon emission and toxic substances from combustion process because the exhaust emission is gathered and controlled in concentrated places. Based on these achievements, the trend of reduction in carbon emissions from the transportation sector has become clear and suggests the need for continued promotion of traffic demand management policies and carbon emission reduction programs (Ko, 2018). During decades, carbon emission per capita in transportation sector reduced more than 35%.

In order to spread environmentally-friendly vehicles, government policies and product design by manufacturers have high priority, and consumers' preferences need to be analyzed. In the early stage of diffusion environment-friendly vehicles such as HEVs and EVs, if government expenses on subsidies for such vehicles, Shin et al., (2012) suggested that people tended to prefer EVs compared to internal combustion vehicles such as gasoline, diesel, and HEVs. Moreover, they suggested that the market potential of EVs was higher than internal combustion engine vehicles, that reduction impact of EVs on carbon emission is more considerable than HEVs and that the cost-benefit effects of subsidies are also

more significant in EVs for carbon emission reduction purposes. In the German case study, Hackbarth and Madlener (2013) analyzed consumer preference for alternative fuel vehicles (AFVs) by mixed logit with interaction terms using discrete choice data from German-wide survey. The German government planned to implement a million EVs on the road by 2020 and Hackbarth, and Madlener (2013) analyzed the feasibility of the implementation via consumer preference analysis. They suggested that German vehicle buyers are reluctant to purchase AFVs and prefer PHEV to EVs. Respondents with a high level of education, deep environmental concerns, and households with possibly installing charging facilities preferred AFVs. Also, scenario analysis showed that current internal combustion engine vehicles will still bring higher levels of market share, and HEVs and natural gas vehicles are relatively preferred among the AFVs. Finally, EV and FCEV were found to be unlikely to spread until strong subsidy policy was introduced. Byun, Shin and Lee (2017) suggested that it is implausible to meet the target for the policy implementation via the price decrease to the level of gasoline vehicles and the number of charging station is increased more than three times compared to the targeted number of charging stations for hydrogen fuel cell vehicles. Also, in 2025, the portion of EV will reach 6.13%, and the portion of HFCV will reach 2.6%. In addition to analyzing the consumer preference toward environment-friendly vehicles, Moon, Park, Jeong, and Lee (2018) derived the change of electricity demand due to the implementation of EVs by analyzing

consumers' charging patterns. They suggested that consumer mainly preferred charging during the evening. Also, during peak load time, people preferred fast public electric vehicle supply equipment (EVSEs) for charging electricity vehicle, which suggested that consumers trade-off between the charging time and the charging price.

These results have drawn implication for the possibility of environment-friendly vehicles and changes in the energy environment caused by the diffusion of these vehicles.

4.3.2 Data Description

For empirical analysis, this dissertation collected data from the hypothesized conjoint survey. The survey was performed on January 2017, conducted face-to-face interviews by Gallup Korea. A total of 418 people participated in the survey, who populated in Seoul and metropolitan area and five major cities (Busan, Incheon, Daegu, Daejeon, and Gwangju). The interviewees were chosen by probability sampling with a quota to have representative demographic characteristics. [4]

The survey processed as follow. First, interviewees were asked about their socio-demographic characteristics, vehicle ownership, and characteristics of

[4] The data used in this dissertation also used in Moon et al. (2018)

owned vehicles. The descriptive statistics of socio-demographic characteristics of survey respondents are shown in Table 40, and attributes in conjoint surveys are suggested in Table 41.

Table 40. Socio-Demographic Characteristics of the EVC Survey Respondents

Characteristics	Frequency or Descriptive Statistics
Gasoline Small Sedan Owner	149/418
Gasoline Large Sedan Owner	132/418
Gasoline SUV Owner	12/418
Diesel SUV Owner	71/418
Knowledge toward transportation policy	Mean: 3.057 Std: 0.818
Current fuel expenditure	Mean: KRW 147.37 K (123.84 USD) Std: KRW 190.42 K (160.02 USD)
Portion of expenditure on car/transportation	Mean: 13.403% Std Dev: 13.016%

The individual socio-demographic such as age and gender, does not affect consumer behavior. Instead, the car types they have, knowledge toward transportation policies, the current expenditure on fuel, and the portion of expenditure on transportation affected the outcome. The number of gasoline small sedan owners, gasoline large sedan owners, gasoline SUV owners, and diesel SUV owners are each 149, 132, 12 and 71 of total 418 individuals. The survey collected knowledge toward transportation policy in 10 questions with 5 Likert-scale questionnaires. The Cronbach's alpha is above 0.8, which suggests that

items could be used as a single scale to measure knowledge toward transportation policy. The mean of current fuel expenditure is KRW 147.37K (123.84 USD), and the standard deviation of current fuel expenditure is KRW 190.42 (160.02 USD) [5]. The mean portion of expenditure on car/transportation is 13.40%, and the standard deviation of the portion is 13.016% (Table 40).

Table 41. Attributes in EVC Conjoint Cards

Attribute	Description	Level
Fuel Type	Fuel types that used	Gasoline(Baseline) Diesel Hybrid Electricity Vehicles (HEVs) Electricity Vehicles (EVs)
Vehicle Body Type	Vehicle segments	Small Size Sedan (Baseline) Mid Size Sedan Luxurious (Full Size) Sedan SUV/RV
Charging Station Accessibility	Distance between charging stations	2Km 10Km 20Km
Fuel Cost	Fuel consumption per unit distance	KRW 50/Km (USD .042/Km) KRW 100/Km (USD .084/Km) KRW 150/Km (USD .127/Km) KRW 200/Km (USD .169/Km)

[5] The currency rate of KRW was KRW 1190/USD (2017. 01), during survey period

Price of Vehicle	Car purchase price	KRW 15 million (USD 12,700) KRW 30 million (USD 25,300) KRW 45 million (USD 38,000) KRW 60 million (USD 50,600)

The attribute was consists of fuel type, vehicle body type, charging station accessibility, fuel costs, and price of purchasing vehicles. The level of fuel type was a gasoline-fueled car (baseline of fuel type attribute), diesel-fueled car, HEVs, and EVs. The level of vehicle body type was Small Size Sedan (Baseline of vehicle body type), mid-size sedan, luxurious (full-size) sedan, and SUV/RV. The charging station accessibility was measured through distance, 2Km, 10Km, and 20Km. Fuel costs per kilometer consisted of four levels, KRW 50/Km (USD .042/Km), KRW 100/Km (USD .084/Km), KRW 150/Km (USD .127/Km), and KRW 200/Km (USD .169/Km). Price of vehicles also consisted of four levels, KRW 15 million (USD 12,700), KRW 30 million (USD 25,300), KRW 45 million (USD 38,000), and KRW 60 million (USD 50,600).

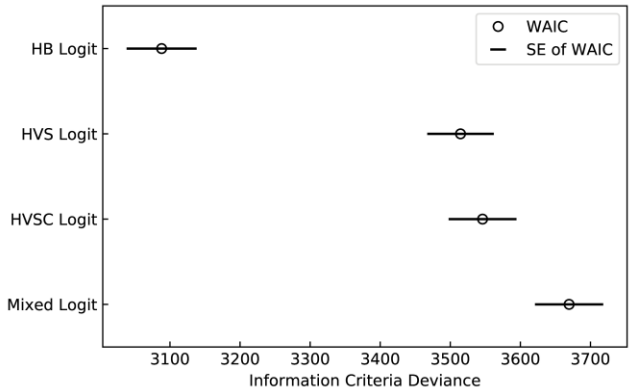
4.3.3 Empirical Results

This section seeks to compare HVSC and HB results, except for the other models. This is because the existing HB with covariates model showed the best model fit than the other models. At first, for the comparison purpose, comparison

of information criterion and log-likelihood of choice probability is shown in table 42. In all cases, WAIC, LOO, and LL, HB covariate logit shows the best performance on VC data compare to all the models (WAIC: 3088.12, LOO: 3621.57, and LL: -937.75). The VC situation in this survey had quite a simple form of an alternative-attribute matrix, which respondents were easily concentrated on all the attributes suggested in the survey. Moreover, VC is quite critical decision-making situation because the vehicle is expensive goods and accounts for a large portion of expenditure in their income level. Therefore, among the VC choice situation in this survey, respondents possibly consider all the attributes suggested in the choice sets.

Table 42. Comparison of Information Criterion of the models (VC)

	WAIC	pWAIC	LOO	pLOO	LL
HB Covariates Logit	3088.12	889.94	3621.57	1156.66	-937.75
HVSC Logit	3546.03	768.41	3766.71	878.75	-1287.50
HVS Logit	3514.58	800.02	3771.92	928.69	-1245.90
HB (Mixed) Logit	3669.53	804.61	3866	902.84	-1324.48



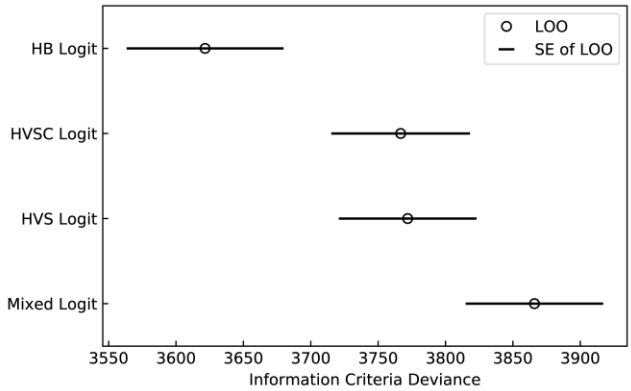


Figure 26. Comparison Diagram of Information Criterion in HVS – WAIC and LOO (VC)

Comparing HB with covariates and HVSC logit model in parallel, the HB logit with covariates showed larger standard deviation in all the pooled parameter, which suggested that the individual utility is widely distributed in all attributes. In some attributes, such as Car cost and Charging station accessibility (CSA), the sensitivity of knowledge toward transportation policy is reduced in the same manner (negative utility coefficients on car cost and CSA and positive covariate coefficients on knowledge toward transportation policy in HB Logit model, negative variable selection coefficients on car cost and CSA). However, it is difficult to compare and place covariates on the same line on both models since the role of covariates is different in both models.

Table 43. Empirical Result of HB with Covariates on VC

	Mean	S.D.	Constant	Gasoline Small Sedan	Gasoline Large Sedan	Gasoline SUV	Diesel SUV	Knowledge toward transportation policy	Current fuel expenditure	Portion of expenditure on car/ transportation
(Baseline: Gasoline)										
Diesel	0.850	0.759	0.878	0.038	-0.238	-0.548	0.213	**0.482**	**0.385**	0.050
Hybrid	0.628	0.727	0.637	**-0.063**	0.279	-1.015	0.178	0.263	**0.477**	0.058
Electricity	0.630	0.736	0.623	0.092	0.113	-0.253	-0.066	**0.391**	**0.324**	**-0.311**
(baseline: Small Size Sedan)										
SUV	0.314	0.750	0.311	-0.399	**-0.815**	**1.097**	-0.028	0.120	0.215	-0.149
Mid size sedan	-0.168	0.758	-0.163	-0.225	**-0.961**	-0.849	-0.515	0.196	-0.297	**-0.353**
Luxurious Sedan	0.098	0.730	0.093	0.003	0.284	0.208	-0.289	0.182	-0.054	-0.018

Fuel Costs	-0.373	0.686	-0.353	-0.072	0.041	0.198	0.222	**0.126**	0.000	0.038
Car cost	-0.484	0.725	-0.490	-0.096	0.089	0.223	0.124	**0.385**	0.103	-0.119
Charging Station Accessibility	-0.131	0.692	-0.133	-0.204	**-0.410**	-0.118	**-0.459**	**0.147**	0.000	**-0.175**
LL	-937.747	135.542								

Bold face refers statistically significance that the p-values are 10% levels

*** Significance at the 1% levels, ** Significance at the 5% levels, * Significance at the 10% levels.

Table 44. Empirical Result of HVSC on VC

	Mean	S.D.	Constant	Gasoline Small Sedan	Gasoline Large Sedan	Gasoline SUV	Diesel SUV	Knowledge toward transportation policy	Current fuel expenditure	Portion of expenditure on car/ transportation
(Baseline: Gasoline)										
Diesel	1.116***	0.290	**0.782**	0.316	0.162	**-1.074**	-0.591	**0.603**	0.195	-0.020
Hybrid	0.943***	0.319								
Electricity	0.983***	0.297								
(baseline: Small Size Sedan)										
SUV	1.078***	0.436	**-1.340**	-0.094	**0.699**	0.897	-0.428	-0.080	**0.411**	**0.452**
Mid size sedan	-0.769 *	0.522								
Luxurious Sedan	0.874***	0.469								
Fuel Costs	-0.876***	0.169	-0.156	**0.655**	0.438	-0.269	-0.353	-0.420	-0.046	0.027
Car cost	-0.872***	0.154	**1.280**	0.432	-0.349	-0.328	-0.323	**-0.619**	-0.335	0.227
Charging Station Accessibility	-0.490***	0.106	-0.177	0.152	0.497	0.154	0.731	**-0.770**	-0.226	0.148
LL	-1287.505	59.331								

Bold face refers statistically significance that the p-values are below 0.1

*** Significance at the 1% levels, ** Significance at the 5% levels, * Significance at the 10% levels.

Table 45. Attribute Attendance/Non-Attendance Patterns in VC

Rank	Fuel Type	Car Type	Fuel Costs	Car Costs	CSA	Frequency
1	1	0	1	1	1	73
2	1	0	0	1	0	62
3	0	0	1	1	1	53
4	1	0	1	1	0	45
5	1	0	0	1	1	36
6	1	0	0	0	0	28
7	0	0	0	1	1	25
8	1	1	0	1	0	11
9	1	0	1	0	0	11
10	1	1	1	1	1	11
11	1	1	0	0	0	10
12	0	1	1	1	1	9
(omit the patterns that frequency is below 9)						
Total	306	64	210	348	235	418
Probability	73.21%	15.31%	50.24%	83.25%	56.22%	

4.3.4 Discussion

This section compared the existing model and the proposed model from the empirical point of view. In the VC case, the results confirmed that the existing model might have a better model fit, in case of simple alternative-attribute formation and the subjective is a good that carefully considered. Above two cases, zero energy house choice situation and telecommunication bundling choice

situation has a better model fit in the suggested models. However, VC cases concluded different results. The results of this section suggest that the appropriate model should be selected comparing existing models and the HVSC models depending on the response characteristics of the data and the characteristics of the data set. If the choice situation has a complex alternative-attribute matrix, or strong preference toward specific attributes and showed exclusion tendency toward specific attributes, then the HVSC model outperforms than the HB with covariates model. However, in case of the simple alternative-attribute matrix that each attribute is important and has wide utility heterogeneity, the empirical results supported the HB with covariates.

Chapter 5. Summary and Conclusion

5.1 Concluding Remarks and Contribution

This dissertation examined the possibility of two different models starting from the same methodological concept and presents empirical analysis results for each model. It suggests a model for explaining consumer ANA behavior considering consumer characteristics and one for identifying individual decision-making behavior heterogeneity between random utility maximization and random regret minimization via Bayesian stochastic search methods. The value of this study lies beyond the heterogeneity of utility and incorporating such decision-making heterogeneity structure into the model. Furthermore, the advantage of these models is that they were devised specifically to explain the heterogeneity of consumers.

This study verified the models through a simulation study conducted via synthetic data and two subsets of empirical data about high tech durable goods, a zero-energy house choice, a telecommunication bundling service choice, and car choice behavior. The validity of the proposed model was confirmed by using synthetic data and the empirical cases were used to support the proposed models in comparison with reference models.

It is hard to generalize the model with three empirical applications. In a complicated choice situation, however, the explanatory power of the HVSC model elicited the best model fits. Furthermore, in the case of simple choice situations where respondents were possibly considering all attributes with wide utility heterogeneity, the conventional HB logit with covariates model elicited the best model fits. In conclusion, based on the dissertation, the HVSC model is expected to show good results when uncertainty is high in high tech goods, and respondents do not understand the properties. On the contrary, it is expected that the HB with covariates model will show better results in high-tech goods that have low uncertainty, and respondents understand the details of the attributes. By contrast, in the HDH model, individual decision-making structures are different given respondents' characteristics and responses toward the choice situation. For certain attributes, respondents will make decisions that maximize their utility and behave as compensatory. Conversely, for other attributes, respondents will as attempt to find appropriate levels of compromise.

5.2 Limitation and Future Studies

The limitations of this study are threefold. First, it is difficult to accurately identify variables that may affect the latent structure identification. Because of the limitations of the variables included in the questionnaire, it was challenging to

determine consumer characteristics that explain the heterogeneous decision-making structure adequately.

Second, and most importantly, the two models are not combined, but are presented separately. The distinctive difference and advantage of this study is that the proposed methodology has not previously been attempted and it showed the potential of using HVSC methods to apply discerning heterogeneous decision-making structures. However, the two alternative decision structures were not combined. Therefore, based on the results of this study, I suggest a hierarchical decision structure model (Figure 27), assuming that a decision-maker has a two-layer decision-making behavior structure.

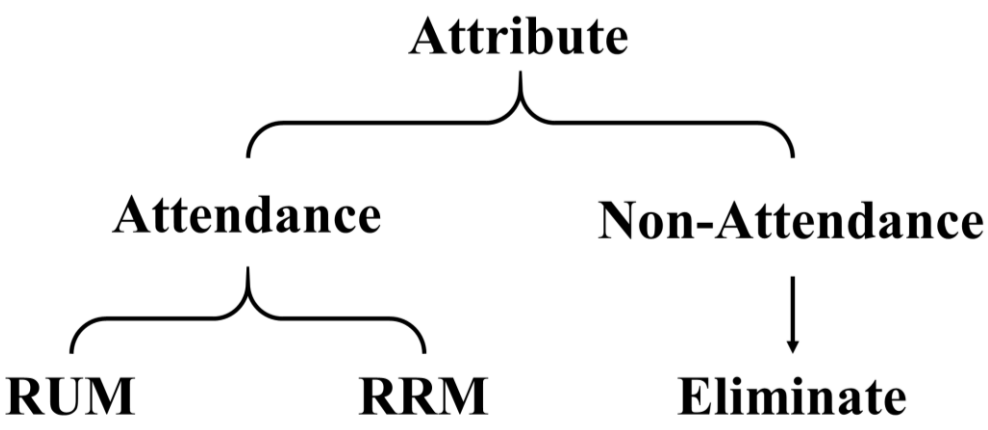


Figure 27. Suggested Topics That Can Be Derived from this Study

The first step is to discern whether the respondents are considering the

variables. It is possible to determine first whether the respondent considered the attribute in the decision-making process. If the respondent did not consider the attribute, the variable can be removed from the respondent's utility structure. If a respondent takes account of the attribute to choose an alternative choice because the attribute is important enough, the next step may be taken. In the second stage, we explore the heterogeneity of decision-making structures. If a respondent exhibits a fully-compensatory behavior and a utility maximization characteristic for the attribute, the attribute will be considered as an RUM. If the respondent has semi-compensatory behavior for the attribute, the attribute should be considered as an RRM.

The last limitation of this dissertation is that the alternative decision-making structure was considered only from the RRM perspective. There are plenty of alternative decision rules in choice modeling (Table 1). It might be worthwhile to allow various alternative decision-making structures within the heterogeneity.

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Appendix 1: Survey Questionnaires for ZEH

H-1. 제로에너지아파트에 대한 선호도

먼저, 제로에너지아파트 및 거주 형태에 대한 질문입니다.

문1. 다음 귀하의 평소 환경에 대한 태도에 대해 귀하와 가장 가까운 번호에 ○표해 주십시오.

	전혀 그렇지 않다 (1)	그렇지 않는 편이다 (2)	보통이다 (3)	그런 편이다 (4)	매우 그렇다 (5)
1. 나는 환경 문제에 관심이 많다	1	2	3	4	5
2. 나는 평소 에너지/환경 문제에 관심이 많다	1	2	3	4	5
3. 나는 세계적인 환경 이슈에 대해 잘 알고 있다	1	2	3	4	5
4. 나는 평소 에너지/환경 정책에 대해 잘 알고 있다	1	2	3	4	5
5. 나는 친환경 제품을 구매하는 것을 좋아한다	1	2	3	4	5
6. 나는 환경오염으로 생태계가 파괴되는 것을 부정적으로 생각한다	1	2	3	4	5
7. 나는 우리나라 환경오염이 심각하다고 생각한다	1	2	3	4	5
8. 나는 우리나라가 에너지/환경 문제에 잘 대처하고 있다고 생각한다	1	2	3	4	5
9. 나는 평소 에너지 절약을 신경쓰는 편이다	1	2	3	4	5
10. 나는 제로에너지아파트에 대해 들어보았거나 알고 있다	1	2	3	4	5

문2. 귀하께서는 집의 온도를 일정하게 유지하기 위해서 가장 중요한 요소는 무엇이라고 생각하십니까?

1. 지속적인 냉방(여름철) 및 난방(겨울철)을 통하여 집 안의 온도를 일정하게 유지한다
2. 우수한 단열재 및 창호를 설치하여 집 안의 온도를 유지한다
3. 춥거나 더운 공기가 들어오지 못하도록 가급적 환기를 자제한다

문3. 귀하께서는 다음 중 어떤 유형의 주택에 살고 계십니까?

1. 단독주택 (빌라, 원룸 등)
2. 오피스텔
3. 대단지 아파트
4. 중소단지 아파트
5. 기타

문4. 귀하께서 살고 계신 주택의 보유 형태는 다음 중 어디에 해당됩니까?

1. 자가 또는 전세
2. 월세 또는 기숙사 등 기타 → 문6.으로 가십시오.

문5. (문4.에서 1. 자가 또는 전세를 응답한 경우만 응답해 주십시오.)
귀하께서 현재 살고 계신 주택의...
- (자기인 경우) 매매 가격(세금을 제외한 현재 혹은 구입 당시의 실 구매가격)과 구입한 시기
- (전세인 경우) 전세 가격과 이주 시기를 응답해 주십시오.

1) 매매 가격 또는 전세 가격

1. 1억 이하
2. 1억~3억 이하
3. 3억~5억 이하
4. 5억~10억 이하
5. 10억 이상

2) 구입 또는 전세 이주시기

[ ][ ][ ][ ] 년 [ ][ ] 월

문6. 귀하께서 현재 살고 계신 **주택의 면적**은 어떻게 됩니까? 공급면적으로 응답해 주십시오.

※ 평수 또는 m^2 중, 귀하께서 알고 계시는 단위 하나에만 응답해 주시면 됩니다. **(1평은 약 3.3m^2 입니다.)**

□□□ 평 또는 □□□ m^2

문7. 귀하께서 현재 살고 계신 집이 **외부 온도**에 어느 정도 **영향**을 받는다고 생각하십니까?

전혀 영향받지 않는다	영향받지 않는 편이다	보통이다	영향받는 편이다	매우 영향 받는다
1	2	3	4	5

문8. 귀하께서는 **하루 시간을 주로** 어떻게 보내십니까? **평일과 휴일로 나누어 응답 시간의 합이 24시간이 되도록 응답**해 주십시오.

1) 평일(월요일~금요일) 24시간 응답란

통근 (출근+퇴근시간)	집에서 생활	여가 시간 (취미 활동)	수면	일과시간 (직장 등에서 보내는 시간 등)	기타	합계
약 □□시간 +	약 □□시간 +	약 □□시간 +	약 □□시간 +	약 □□시간 +	약 □□시간 =	24시간

2) 휴일(토요일~일요일 및 공휴일) 24시간 응답란

통근 (출근+퇴근시간)	집에서 생활	여가 시간 (취미 활동)	수면	일과시간 (직장 등에서 보내는 시간 등)	기타	합계
약 □□시간 +	약 □□시간 +	약 □□시간 +	약 □□시간 +	약 □□시간 +	약 □□시간 =	24시간

문9. 귀하께서는 **1년 중 전기료와 난방비**가 가장 많이 나오는 달에 얼마를 지불하십니까?

1) **전기료** 약 □□만 □천원

2) **난방비** 약 □□만 □천원

H-2. 제로에너지아파트 유형별 선호도

1. 지금부터는 **제로에너지아파트가 전국적으로 확대**되었을 때, **귀하의 선호도**를 묻는 질문입니다.
2. 응답하실 유형별 선호도 질문은
   ① **주거 유형 설명문** (주거 선택 시 고려해야할 여러 속성과 속성별 수준에 대한 설명)과
   ② **제로에너지아파트 유형별 선호 순위를 묻는 질문**과 **가장 선호하는 유형 질문**이 제시됩니다.

먼저 **주거 유형별 속성 및 수준 설명문을 숙지**한 후, 다음 페이지 질문에 응답해 주십시오.

▣ 주거 유형별 속성 및 수준 설명문

속성		속성 설명 및 수준
1. 시공 건설사의 크기/종류	설명	제로에너지아파트를 **시공한 건설사의 크기**를 의미합니다.
	수준 (2개)	① 대형 건설사 (레미안, 자이, 아이파크, 롯데캐슬, 프루지오, 더샵 등) ② 중소형 건설사 (코아루, 사랑으로, 어울림, 반도유보라 등)
2. 대중교통 및 학교와의 접근성	설명	**대중교통과 학교로부터의 도보거리**를 뜻합니다.
	수준 (3개)	① 도보로 5분 (약 500m 내에 학교와 대중교통이 존재함) ② 도보로 10분 (약 1km 내에 학교와 대중교통이 존재함) ③ 도보로 15분 (약 1.5km 내에 학교와 대중교통이 존재함)
3. 신재생에너지 발전설비 설치여부	설명	아파트 단지 전체에 **지열 및 태양광 발전설비를 설치**할 수 있습니다.
	수준 (2개)	① 설치한다 ② 설치하지 않는다
4. 환기 방법	설명	실내 공기를 쾌적하게 유지하기 위해서는 환기가 필수적입니다. **환기를 하는 방법**에는 자연 환기, 일반 기계식 환기, 열교환식 환기가 있습니다.
	수준 (3개)	① 자연 환기 (창문 개폐를 통한 환기입니다) ② 일반 기계식환기 (일반적인 환기 시스템으로, 창문의 개폐가 없이 밖의 공기를 안으로 들여오고 내부의 공기를 밖으로 배출합니다) ③ 열교환식 환기 (일반 기계식 환기와 비교하여 집 내부의 온도를 일정하게 유지하는데 유리합니다)
5. 연간 감축 가능한 이산화탄소의 양	설명	제로에너지건축물로 인증을 받은 아파트에 거주하는 경우, 친환경 아파트로써 **화석연료의 사용으로 인한 이산화탄소의 배출량을 크게 감소**시킬 수 있습니다.
	수준 (3개)	① 가구당 이산화탄소 배출량 연간 1.2톤 감축 (1년에 30살 소나무 약 200그루 심는 것과 같은 효과) ② 가구당 이산화탄소 배출량 연간 4.8톤 감축 (1년에 30살 소나무 약 770그루 심는 것과 같은 효과) ③ 가구당 이산화탄소 배출량 연간 8.4톤 감축 (1년에 30살 소나무 약 1,350그루 심는 것과 같은 효과)
6. 절약 가능한 전기료 및 난방비용	설명	제로에너지건축물로 인증을 받은 아파트에 거주하는 경우, **전기세와 난방비용을 절약**할 수 있습니다. (30평 기준, 전기료 및 난방비용은 월 평균 173,000원입니다.)
	수준 (3개)	① 30% 절약 (30평 기준, 30% 절약할 시, **월 평균 51,900원 절약 가능**) ② 60% 절약 (30평 기준, 60% 절약할 시, **월 평균 103,800원 절약 가능**) ③ 90% 절약 (30평 기준, 90% 절약할 시, **월 평균 155,700원 절약 가능**)
7. 집의 평당 가격 증가 정도	설명	현재 거주하고 있는 집의 **평당 가격 대비 증가하는 정도**입니다.
	수준 (3개)	① 평당 100만원 증가 (30평 기준, 집의 가격 약 3,000만원 증가) ② 평당 200만원 증가 (30평 기준, 집의 가격 약 6,000만원 증가) ③ 평당 300만원 증가 (30평 기준, 집의 가격 약 9,000만원 증가)

지금부터 앞에서 설명해드린 주거 선택 관련 속성을 조합하여 구성한 **가상의 주거 유형 3개와 기존과 동일한 주거 유형을 동시에 제시한 질문 4개**가 제시됩니다. 귀하께서는 각 질문별로,

① 선호하는 순서대로 **유형의 순위를 1위부터 3위까지** 응답해 주시고,

② 기존과 동일한 주거 유형이 포함된 4개의 주거 유형 중, **가장 선호하는 유형 하나에 O표**해 주시면 됩니다.

※ 귀하께서 현재 살고 있는 주택과 동일한 행정구역 내에서 주거를 이전하고자 하며, 아래 제시된 속성 이외의 다른 모든 조건들은 동일하다는 가정 하에 응답해주십시오. (예시: 세종시 30평 개인주택에 거주하는 가구는 동일한 행정구역인 세종시 내에 있는 30평 아파트를 구매하여 이사함)

※ 현재 전세/월세 등 임대나 자가 주택 여부와 관계없이, 같은 지역 내 비슷한 크기의 아파트를 구매하여 이사를 간다는 가정 하에 응답해 주십시오. (예시: 40평 월/전세 공동주택에 거주하는 가구는 40평 아파트를 구매하여 이사함)

구분		유형 A	유형 B	유형 C	유형 D
질문 1	1. 시공 건설사의 크기	대형건설사 시공	중소형건설사 시공	중소형건설사 시공	추가비용을 부담하지 않고 기존에 살던 집과 비슷한 집을 선택한다
	2. 학교/교통수단 접근성	도보 10분거리 (1km)	도보 5분거리 (500m)	도보 15분거리 (1.5km)	
	3. 신재생에너지 발전설비	발전설비 설치	발전설비 미설치	발전설비 미설치	
	4. 환기 방법	자연환기	일반 기계식환기	자연환기	
	5. 이산화탄소 연간 감축량	연 1.2t 감축	연 1.2t 감축	연 4.8t 감축	
	6. 전기세/난방비 절약	60% 절약가능	30% 절약가능	90% 절약가능	
	7. 집의 평당 가격 상승	300만원 상승	200만원 상승	200만원 상승	
1위~3위까지 선호 순위 응답란 →		□ 위	□ 위	□ 위	
가장 선호하는 유형 응답란 → (4개 유형 중, 하나에 O표)		유형 A	유형 B	유형 C	유형 D

구분		유형 A	유형 B	유형 C	유형 D
질문 2	1. 시공 건설사의 크기	대형건설사 시공	중소형건설사 시공	중소형건설사 시공	추가비용을 부담하지 않고 기존에 살던 집과 비슷한 집을 선택한다
	2. 학교/교통수단 접근성	도보 10분거리 (1km)	도보 5분거리 (500m)	도보 15분거리 (1.5km)	
	3. 신재생에너지 발전설비	발전설비 미설치	발전설비 미설치	발전설비 설치	
	4. 환기 방법	열교환식 환기	자연환기	자연환기	
	5. 이산화탄소 연간 감축량	연 1.2t 감축	연 4.8t 감축	연 8.4t 감축	
	6. 전기세/난방비 절약	30% 절약가능	60% 절약가능	30% 절약가능	
	7. 집의 평당 가격 상승	300만원 상승	300만원 상승	200만원 상승	
1위~3위까지 선호 순위 응답란 →		□ 위	□ 위	□ 위	
가장 선호하는 유형 응답란 → (4개 유형 중, 하나에 O표)		유형 A	유형 B	유형 C	유형 D

구분		유형 A	유형 B	유형 C	유형 D
질문 3	1. 시공 건설사의 크기	대형건설사 시공	중소형건설사 시공	중소형건설사 시공	추가비용을 부담하지 않고 기존에 살던 집과 비슷한 집을 선택한다
	2. 학교/교통수단 접근성	도보 5분거리 (500m)	도보 15분거리 (1.5km)	도보 15분거리 (1.5km)	
	3. 신재생에너지 발전설비	발전설비 설치	발전설비 설치	발전설비 미설치	
	4. 환기 방법	지연환기	열교환식 환기	일반 기계식환기	
	5. 이산화탄소 연간 감축량	연 4.8t 감축	연 8.4t 감축	연 4.8t 감축	
	6. 전기세/난방비 절약	30% 절약가능	30% 절약가능	60% 절약가능	
	7. 집의 평당 가격 상승	300만원 상승	300만원 상승	100만원 상승	
1위~3위까지 선호 순위 응답란 →		□ 위	□ 위	□ 위	
가장 선호하는 유형 응답란 → (4개 유형 중, 하나에 O표)		유형 A	유형 B	유형 C	유형 D

구분		유형 A	유형 B	유형 C	유형 D
질문 4	1. 시공 건설사의 크기	대형건설사 시공	중소형건설사 시공	중소형건설사 시공	추가비용을 부담하지 않고 기존에 살던 집과 비슷한 집을 선택한다
	2. 학교/교통수단 접근성	도보 10분거리 (1km)	도보 10분거리 (1km)	도보 5분거리 (500m)	
	3. 신재생에너지 발전설비	발전설비 설치	발전설비 미설치	발전설비 설치	
	4. 환기 방법	자연환기	일반 기계식환기	자연환기	
	5. 이산화탄소 연간 감축량	연 4.8t 감축	연 8.4t 감축	연 4.8t 감축	
	6. 전기세/난방비 절약	90% 절약가능	60% 절약가능	30% 절약가능	
	7. 집의 평당 가격 상승	300만원 상승	200만원 상승	100만원 상승	
1위~3위까지 선호 순위 응답란 →		☐ 위	☐ 위	☐ 위	
가장 선호하는 유형 응답란 → (4개 유형 중, 하나에 ○표)		유형 A	유형 B	유형 C	유형 D

문5. 다음은 귀하께서 위의 선호도 질문에 응답하면서 비교한 **각 속성별 고려 수준**에 대한 질문입니다.
위 질문에 응답하면서 귀하께서 각 속성에 대해 고려한 수준을 **5점 척도로 응답**하여 주시기 바랍니다.

	전혀 고려하지 않았다. (1)	고려하지 않은 편이다. (2)	보통이다 (3)	대체로 고려했다. (4)	매우 고려했다. (5)
1. 시공 건설사의 크기	1	2	3	4	5
2. 학교/교통수단 접근성	1	2	3	4	5
3. 신재생에너지 발전설비	1	2	3	4	5
4. 환기 방법	1	2	3	4	5
5. 이산화탄소 연간 감축량	1	2	3	4	5
6. 전기세/난방비 절약	1	2	3	4	5
7. 집의 평당 가격 상승	1	2	3	4	5

문6. 귀하께서 지금까지 응답하신 제로에너지아파트 유형에 대해 **제로에너지아파트의 각 속성별로 귀하께서 기대하는 수준 (특정 수준을 만족하지 않을 경우 선택하지 않는 수준)**을 응답해 주십시오.

제로에너지아파트 속성	기대하는 제로에너지아파트 수준 응답란
1. 시공 건설사의 크기/종류 (1. 또는 2. 중 하나 응답)	1. 대형 건설사 (레미안, 자이, 아이파크, 롯데캐슬, 프루지오, 더샵 등) 2. 중소형 건설사 (코아루, 사랑으로, 어울림, 반도유보라 등)
2. 대중교통 및 학교와의 접근성 (시간 응답)	도보로 최대 ☐☐ **분 이내**
3. 신재생에너지 발전설비 설치여부 (1. 또는 2. 중 하나 응답)	1. 설치한다 2. 설치하지 않는다
4. 환기 방법 (1., 2. 또는 3. 중 하나 응답)	1. 자연 환기 (창문 개폐를 통한 환기) 2. 일반 기계식 (창문의 개폐 없이 밖의 안과 밖의 공기를 순환시킴) 3. 열교환식 (일반 기계식 보다 집 내부의 온도를 일정하게 유지하는데 유리)
5. 연간 감축 가능한 이산화탄소의 양 (그루 응답)	가구당 1년에 30살 소나무 ☐☐☐ **그루 이상** 심는 효과
6. 절약 가능한 전기료 및 난방비용 (비율 응답)	현재 대비 최소 ☐☐ **% 이상** 절약
7. 집의 평당 가격 증가 정도 (금액 응답)	평당 ☐☐☐ **만원 이하** 증가

I. 자료 분류용 질문

마지막으로 응답자 분류를 위한 질문입니다.

I1. 귀하의 **직업**은 어떻게 됩니까?

1. 자영업 (종업원 9명이하 소규모업소 주인/가족종사자)
2. 판매/서비스직 (상점점원, 세일즈맨 등)
3. 기능/숙련공 (운전사, 선반/목공, 숙련공 등)
4. 일반작업직 (토목 현장작업/청소/수위/육체노동 등)
5. 사무/기술직 (일반회사 사무직/기술직, 교사 등)
6. 경영/관리직 (5급 이상 공무원/기업체 부장 이상 등)
7. 전문/자유직 (대학교수/의사/변호사/예술가/종교가 등)
8. 전업주부
9. 학생
10. 무직
11. 기타 (구체적으로 응답해 주십시오 : _____)

I2. 귀하의 **최종학력**은 어떻게 됩니까?

1. 중/고등학교 졸업
2. 전문대 졸업
3. 대학교 졸업
4. 대학원 졸업

I3. 현재 귀 댁의 **월 평균 소득 수준**은 얼마나 됩니까? 세금은 제외한 **보너스, 이자수입 등 모든 수입**을 합해서 응답해 주십시오.

1. 99만원 이하
2. 100만원~149만원 이하
3. 150만원~199만원 이하
4. 200만원~249만원 이하
5. 250만원~299만원 이하
6. 300만원~399만원 이하
7. 400만원~499만원 이하
8. 500만원~699만원 이하
9. 700만원~999만원 이하
10. 1,000만원 이상

I4. 그럼, 현재 귀 댁의 **월 평균 소비 지출**은 얼마나 됩니까?

☐ 천 ☐ 백 ☐ 십 ☐ 만원 정도

I5. **[개인정보 수집, 이용 동의] 응답 확인 등 검증에 필요한 개인정보 수집 동의에 대해 여쭙겠습니다.**
① 개인정보의 수집·이용 목적 : 응답자 확인, 응답 확인, 답례제공 여부 확인 등 검증을 위한 개인정보 수집·이용
② 수집하려는 개인정보의 항목 : 응답자 성명, 응답자 연락처
③ 개인정보의 보유 및 이용기간 : 검증 후 6개월
위 개인정보 수집에 동의하십니까? 동의를 거부할 권리가 있습니다.

1. 동의함
2. 동의 안함

★ 끝까지 응답해 주셔서 대단히 감사합니다 ★

면 접 후 기 록			
응답자 성명		응답자 연락처	
조 사 일 시	___월 ___일	면접원 성명	(ID: _____)
실사 검증원	(ID: _____)	실사 연구원	(ID: _____)

Appendix 2: Survey Questionnaires for TBC

D. 유료방송 서비스 사용현황 및 태도

문1. 귀댁에서 지난 **2010년부터 2016년까지 이용한 유료방송 서비스**에 대해...
1) 년도별로 이용한 유료방송 서비스 세부상품 (보기카드의 번호입력)과
2) **(케이블TV인 경우)** 해당하는 케이블TV 사업자의 지역별로 사업자 코드를 각각 응답해 주십시오.

※ 해당년도에 유료방송 서비스를 사용하지 않은 경우, 0으로 입력해 주십시오.

※ - 귀하께서는 **2페이지 문1.번에서 현재 사용중인 유료방송 서비스를 응답**하셨습니다.
- 케이블TV는 지역별로 사업자가 정해져 있으므로, 보기카드의 지역별 케이블TV 사업자 정보를 참고해 주십시오.
- 연 중간에 유료방송 서비스를 바꾼 경우 **당해 년도 마지막에 이용한 유료방송 서비스를 응답**해 주시고, 한해에 사용한 유료방송 서비스가 2개 이상인 경우, 주사용 유료방송 서비스를 응답해 주십시오.

※ 보기카드의 유료방송 서비스 세부상품은 2016년 기준으로 구성되어 있습니다.

※ 유료방송 서비스 세부상품이나 지역별 케이블TV 사업자 등을 잘 모르시거나, 귀댁에서 이전에 사용하시거나 현재 사용중인 유료방송 서비스와 정확하게 일치하지 않는 경우에도, **대략적으로 가장 가까운 세부상품과 케이블TV 사업자 정보를 년도별로 꼭 응답**해 주십시오.

▣ 최근 7년간 유료방송 서비스 사용현황 응답란

년도	1) 년도별 유료방송 서비스 세부상품 (보기카드의 코드번호 입력)	2) 년도별 지역별 케이블TV 사업자 (보기카드의 코드번호 입력)
2010년	□□ - □ - □□	□□ - □□
2011년	□□ - □ - □□	□□ - □□
2012년	□□ - □ - □□	□□ - □□
2013년	□□ - □ - □□	□□ - □□
2014년	□□ - □ - □□	□□ - □□
2015년	□□ - □ - □□	□□ - □□
2016년	□□ - □ - □□	□□ - □□

다음은 귀하의 채널 시청행동과 콘텐츠 선호도를 묻는 질문입니다.

문5. 귀하의 주중 (월~금요일)과 주말 (토/일요일)별 1일 평균 TV시청 시간에 대해...
1) **전체 TV시청 시간**과,
2) 지상파 채널, 종편/보도채널과 일반PP채널의 **세부 채널별 시청시간**을 각각 응답해 주십시오.

※ 시청시간은 **10분 단위로 응답해 주십시오.**

채널 구분	세부 채널	주중(월~금요일) 1일 평균 시청시간	주말(토/일요일) 1일 평균 시청시간
지상파 채널	KBS1	시간 0 분	시간 0 분
	KBS2	시간 0 분	시간 0 분
	MBC	시간 0 분	시간 0 분
	SBS (SBS 계열 민방 포함)	시간 0 분	시간 0 분
	EBS	시간 0 분	시간 0 분
종편/보도채널	JTBC	시간 0 분	시간 0 분
	채널A	시간 0 분	시간 0 분
	TV조선	시간 0 분	시간 0 분
	매일경제TV(MBN)	시간 0 분	시간 0 분
	YTN	시간 0 분	시간 0 분
	연합뉴스TV	시간 0 분	시간 0 분
일반PP채널	드라마, 예능 채널 (tvN, 올리브TV MBC 드라마넷 등)	시간 0 분	시간 0 분
	음악 채널 (Mnet, KMTV 등)	시간 0 분	시간 0 분
	영화, 애니메이션 채널 (채널CGV, 투니버스 등)	시간 0 분	시간 0 분
	스포츠 채널 (ESPN, SPOTV, XTM 등)	시간 0 분	시간 0 분
	정보 채널 (증권방송, 육아방송, 국방TV 등)	시간 0 분	시간 0 분
	외신 채널 (BBC world, CCTV 등)	시간 0 분	시간 0 분
	홈쇼핑 채널 (GS 홈쇼핑, 롯데홈쇼핑 등)	시간 0 분	시간 0 분

문2. (문2.는 2페이지 문1.에서 현재 유료방송 서비스를 사용하는 경우만 응답해 주십시오.)
다음은 귀댁에서 **현재 유료방송 서비스를 가입하게 된 계기 (이유)**를 묻는 질문입니다. 아래 질문별로, 귀댁과 **가장 가까운 번호에** ○표해 주십시오.

	전혀 영향이 없었다	영향이 없는 편이었다	보통 이었다	영향이 많은 편이었다	매우 영향이 있었다
	1	2	3	4	5
1. **지상파 방송 채널을 수신**하기 위해서	1	2	3	4	5
2. **지상파 방송** 시청은 가능하나, 보다 **선명한 화질로 보기** 위해서	1	2	3	4	5
3. **종편 채널을 시청**하기 위해서 (TV조선, JTBC, 채널A 등)	1	2	3	4	5
4. **종편 외 다양한 유료방송 채널**을 시청하기 위해서 (TVN, OCN 등)	1	2	3	4	5
5. VOD (다시보기)를 시청하기 위해서	1	2	3	4	5
6. **양방향 서비스**를 이용하기 위해서	1	2	3	4	5
7. **현재 통신회사의 결합상품**으로 인한 추가 할인 때문에	1	2	3	4	5

문3. (문3.은 앞 페이지에서 2010년 이후, 유료방송 서비스 유형을 변경한 경우만 응답해 주십시오.)
다음은 귀댁에서 **이전 유료방송 서비스에서 현재 유료방송 서비스로 바꾸게 된 계기 (이유)**를 묻는 질문입니다.
아래 질문별로, 귀댁과 **가장 가까운 번호에** ○표해 주십시오.
※ 유료방송 서비스 바꾼 경험이 여러 번 있는 경우, **가장 최근을 기준으로 응답**해 주십시오.

	전혀 영향이 없었다	영향이 없는 편이었다	보통 이었다	영향이 많은 편이었다	매우 영향이 있었다
	1	2	3	4	5
1. **현재 사용하는 통신회사의 결합상품**으로 인한 추가 할인 혜택 때문에	1	2	3	4	5
2. 이전에 사용하던 **유료방송 서비스의 사용요금**이 비싸서	1	2	3	4	5
3. 이전에 사용하던 **유료방송 서비스의 품질**이 좋지 않아서	1	2	3	4	5
4. (이사 등의 이유로) 더 이상 **기존 서비스 사용이 불가능**해서	1	2	3	4	5

문4. (문4.는 2페이지 문1.에서 현재 유료방송 서비스를 사용하지 않는 경우만 응답해 주십시오.)
다음은 귀댁에서 **현재 유료방송 서비스를 사용하지 않는 이유**를 묻는 질문입니다. 아래 질문별로, 귀댁과 **가장 가까운 번호에** ○표해 주십시오.

	전혀 영향이 없다	영향이 없는 편이다	보통 이다	영향이 많은 편이다	매우 영향이 있다
	1	2	3	4	5
1. **지상파 수신이 원활**해서 (화질 저하 및 끊김 문제 없음)	1	2	3	4	5
2. **주 시청 채널이 지상파**로 한정 되서	1	2	3	4	5
3. 유료방송 서비스 **설치비**가 비싸서	1	2	3	4	5
4. 유료방송 서비스 **월 이용료**가 비싸서	1	2	3	4	5
5. 유료방송 채널 중에서 **볼만한 프로그램**이 없어서	1	2	3	4	5
6. 유료방송 사업자의 **서비스**가 마음에 들지 않아서	1	2	3	4	5
7. **자녀의 잦은 TV 시청**이 걱정 되서	1	2	3	4	5
8. **TV 시청 빈도**가 낮아서	1	2	3	4	5

문6. (문6.은 현재 유료방송 서비스를 사용하는 경우만 응답해 주십시오.)
초고속인터넷, 집전화 (유선전화/인터넷전화)와 귀하의 이동전화별로 현재 사용중인 유료방송 서비스와 함께 결합상품으로 이용하는지 여부를 각각 응답해 주십시오.

※ 결합상품 설명문
초고속인터넷, 이동전화, 집전화 (유선전화/인터넷전화), IPTV나 케이블TV 등 한 회사의 여러 방송 또는 통신 서비스를 패키지 형태로 일정 요금을 할인받고 사용하는 상품

	응 답 란	
1. 초고속인터넷 ·····	1. 유료방송과 함께 결합상품으로 사용	2. 유료방송과는 별개로 단독 사용
2. 집전화 (유선전화/인터넷전화) ·····	1. 유료방송과 함께 결합상품으로 사용	2. 유료방송과는 별개로 단독 사용
3. 응답자 이동전화 ·····	1. 유료방송과 함께 결합상품으로 사용	2. 유료방송과는 별개로 단독 사용

문7. ① 제시한 3개의 결합 상품 (유료방송 서비스 및 이동전화) 유형 중, 선호 순위를 1위부터 3위까지 응답해 주시고, ② 선호하는 결합상품 서비스 없음/현재 서비스 이용이 포함된 4개의 유료방송 서비스 유형 중, 가장 선호하는 유형 하나에 O표해 주십시오.

▣ 결합상품 서비스 선호도 질문 1

서비스 속성 구분	유형 A	유형 B	유형 C	비선택
1. 계약 (약정) 기간	3년	3년	2년	선호하는 서비스 없음 / 현재 서비스 이용
2. 이동통신 서비스 사업자	KT	LG U+	LG U+	
3. 이동통신요금 할인 정도	30%	10%	20%	
4. 유료방송 서비스 할인 정도	10%	50%	10%	
① 선호 순위 응답란 (1위부터 3위까지 응답 →)				
② 가장 선호하는 유형 응답란 (4개 중 하나에 ○표 →)	유형 A	유형 B	유형 C	비선택

▣ 결합상품 서비스 선호도 질문 2

서비스 속성 구분	유형 A	유형 B	유형 C	비선택
1. 계약 (약정) 기간	2년	1년	1년	선호하는 서비스 없음 / 현재 서비스 이용
2. 이동통신 서비스 사업자	KT	SKT	KT	
3. 이동통신요금 할인 정도	10%	10%	20%	
4. 유료방송 서비스 할인 정도	90%	10%	50%	
① 선호 순위 응답란 (1위부터 3위까지 응답 →)				
② 가장 선호하는 유형 응답란 (4개 중 하나에 ○표 →)	유형 A	유형 B	유형 C	비선택

▣ 결합상품 서비스 선호도 질문 3

서비스 속성 구분	유형 A	유형 B	유형 C	비선택
1. 계약 (약정) 기간	2년	1년	3년	선호하는 서비스 없음 / 현재 서비스 이용
2. 이동통신 서비스 사업자	SKT	LG U+	SKT	
3. 이동통신요금 할인 정도	30%	30%	20%	
4. 유료방송 서비스 할인 정도	50%	90%	90%	
① 선호 순위 응답란 (1위부터 3위까지 응답 →)				
② 가장 선호하는 유형 응답란 (4개 중 하나에 ○표 →)	유형 A	유형 B	유형 C	비선택

Appendix 3: Survey Questionnaires for VC

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GMR2016-141-037

전기자동차 및 충전소에 대한 인식 조사

안녕하십니까?

한국갤럽조사연구소에서는 서울대학교 기술경영경제정책 대학원의 의뢰로 일반국민 여러분의 **전기자동차 및 충전소**에 대한 인식과 **선호**를 알아보고 있습니다. 본 질문에는 맞고 틀리는 답이 없으며, 이런 의견을 갖고 있는 사람이 몇 퍼센트 (%)라는 식으로 통계를 내는 데에만 사용되며, 그 외의 목적에는 절대로 사용되지 않으니 평소 생각대로 응답해 주시면 됩니다. 또한, 귀하께서 응답해 주신 내용은 통계법(제33조)에 따라 통계목적으로만 사용되며, 귀하의 의견은 철저히 보호됨을 약속드립니다. 바쁘시겠지만, 조사에 협조해 주시면 대단히 감사드리겠습니다.

2016년 12월
한국갤럽조사연구소
박 무 익

문1. 성별 :

1. 남자 2. 여자

문2. 실례지만, 귀하의 **올해 만 나이**(=2016-출생년도)는 어떻게 되십니까?

만 [ ][ ] 세 → **만20~59세 사이만 조사 진행**

문3. 귀하께서 현재 살고 계신 지역은 어디입니까?

01. 서울 02. 부산
03. 대구 04. 인천
05. 광주 06. 대전
07. 울산 08. 세종
09. 경기 10. 강원
11. 충북 12. 충남
13. 전북 14. 전남
15. 경북 16. 경남 17. 제주

문4. 귀하께서 **현재 살고 계신 지역**에 거주하신지는 **얼마나** 되셨습니까?

[ ][ ] 년 [ ][ ] 개월 째 거주중

- 1 -

A. 자동차 전반에 대한 보유 및 사용 행태

다음은 자동차 전반에 대한 보유 및 사용 행태를 묻는 질문입니다.

문1. 현재 귀하께서는 **자동차 운전면허**가 있으십니까?

1. 예 (있다)
2. 아니오 (없다)

문2-1. 그럼, 귀하께서는 평소에 **자동차를 직접 운전**하고 계십니까? 귀하 또는 귀 댁 소유의 차가 아니어도 되며, 자동차를 직접 운전하시는 여부를 묻는 질문입니다.

1. 예 (운전한다)
2. 아니오 (운전하지 않는다) → **문3-1.으로 이동**

문2-2. **(문2-1.에서 1. 예 (운전한다)에 응답한 경우만 제시)**
그럼, 귀하의 **운전경력은 대략 몇 년**이나 됩니까?

약 [ ][ ] 년

문3-1. **(전체 응답자 모두에게 제시)**
현재 귀댁에서는 **자동차를 보유**하고 있습니까?

1. 예 (있다)
2. 아니오 (없다) → **문5-1.로 이동**

문3-2. **(문3-1.에서 1. 예에 응답한 경우만 제시)**
그럼, 귀댁에서는 **자동차를 모두 몇 대나 보유**하고 있습니까?

1. 1 대
2. 2 대 이상

문4. (문3-2.에서 응답한 대수만큼 제시)
귀댁에서 현재 보유하고 있는 자동차에 대해 ① 차종, ② 연료유형, ③ 연식(제조년도), ④ 구매년도, ⑤ 자동차 구매가격과 ⑥ 신규 또는 교체 구매 여부에 응답해 주십시오.

※ 만약, 현재 보유중인 자동차가 2대 이상인 경우, 주사용 차량을 먼저 응답해 주십시오.

※ 신규/교체여부 응답시 주의사항

1. 신규는 이전에 차를 보유하고 있지 않다가 차량을 신규로 구매한 경우 또는 1대 만을 보유하다가 추가로 2번째 차량을 구매한 경우에 응답
2. 교체는 이전에 차량을 1대 또는 2대 보유하다가 차량을 처분하고 그것을 대체하는 차량을 구매한 경우에 응답

※ 신규/교체여부 응답예시

▷ (소비자 1)
- 2007년에 아반떼를 신규로 구매하여 운행하던 소비자가
- 2010년에 아반떼를 처분하고 소나타를 구매하였고, (소나타는 아반떼 교체구매)
- 2014년에 모닝을 새롭게 구매한 경우, (모닝은 신규구매)

현재 보유 차량은 소나타와 모닝으로, 소나타는 2. 교체, 모닝은 1. 신규에 응답

▷ (소비자 2)
- 2009년에 스포티지를 신규로 구매하여 운행하던 소비자가
- 2011년에 SM3를 신규로 구입하였고,
- 2015년에 SM3를 처분하고 말리부를 새롭게 구매한 경우

현재 보유차량은 스포티지와 말리부로, 스포티지는 1. 신규구매, 말리부는 2. 교체구매에 응답

번호	차종	연료유형	연식(제조년도)	구매년도	구매가격 (단위 : 만원)	신규/교체구매 여부
1	1. 경차 2. 소형차 3. 준중형차 4. 중형차 5. 대형차 6. SUV/RV 7. 기타	1. 휘발유 2. 경유 3. 하이브리드(HEV) 4. 전기차			____만원	1. 신규구매 2. 교체구매
2	1. 경차 2. 소형차 3. 준중형차 4. 중형차 5. 대형차 6. SUV/RV 7. 기타	1. 휘발유 2. 경유 3. 하이브리드(HEV) 4. 전기차			____만원	1. 신규구매 2. 교체구매

주1) 차종구분
1. 경차 (배기량 1,000cc 미만 : 기아 레이/모닝, 쉐보레 스파크 등)
2. 소형차 (배기량 1,000cc 이상~1,600cc 미만 : 현대 액센트, 기아 프라이드, 쉐보레 아베오 등)
3. 준중형차 (배기량 1,300cc 이상~1,600cc 이하 : 현대 아반떼, 기아 K3, 르노삼성 SM3 등)
4. 중형차 (배기량 1,600cc 이상~2,000cc 미만 : 현대 소나타, 기아 K5, 쉐보레 말리부 등)
5. 대형차 (배기량 2,000cc 이상 : 현대 제네시스/에쿠스, 기아 K7/9, 쉐보레 알페온 등)
6. SUV/RV

주2) 하이브리드(HEV) 및 전기차
하이브리드 차량은 휘발유/경유를 주 연료로 하며 엔진 사용 시 발생하는 에너지로 활용해 전기모터를 함께 이용하는 차량임
(예시): 쏘나타 하이브리드, K5 하이브리드, 레이 바이퓨얼, 토요타 프리우스 등
전기 차량은 전기만을 연료로 이용하는 차량으로, 4~8시간의 완속 충전이나 10~30분의 급속 충전이 필요함
(예시): 스파크 EV, 닛산 리프 EV, BMW i3, 테슬라 모델S 등

B. 자동차 유형별 선호도

다음은 자동차의 여러 속성과 속성별 수준에 대한 설명입니다. 본 조사에서는 현재 시장에서 본격적으로 시판되고 있지 않은 전기자동차를 대안으로 포함하여 신차구입에 대한 선호도를 알아보고 있습니다. 다음 제시한 속성 설명을 숙지하시고 응답해 주시기 바랍니다.

▣ 자동차 속성 및 수준 설명문

속성		속성 설명 및 수준
1. 연료 비용	설명	**연료비용은 1Km 주행 시 소요되는 비용을 의미함.** (월 연료비용은 국내에서 운행 중인 차량의 월평균 주행거리를 1300km를 적용하여 계산한 결과임)
	수준 (4개)	① 50원/km (65,000원/월) ② 100원/km (130,000원/월) ③ 150원/km (195,000원/월) ④ 200원/km (260,000원/월)
2. 차량 가격	설명	**차량가격은 차량 등록세, 취득세 등 세금을 포함한 차량 구매에 소요되는 총 비용을 의미함.** (현재 국내 등록세는 차량 가격의 3~5%, 취득세는 차량 가격의 2% 수준임)
	수준 (4개)	① 1,500만원 ② 3,000만원 ③ 4,500만원 ④ 6,000만원
3. 연료 종류	설명	**차량의 연료종류는 휘발유, 경유, 하이브리드(휘발유+전기), 전기(배터리)로 구분됨** - **휘발유, 경유** 차량은 일반적으로 유류만을 연료로 사용하는 내연기관차임 - 하이브리드 차량은 휘발유/경유를 주 연료로 하며, 엔진 사용 시 발생하는 에너지로 활용해 전기모터를 함께 이용하는 차량임 - **전기** 차량은 전기만을 연료로 이용하는 차량으로, 4~8시간의 완속 충전이나 10~30분의 급속 충전이 필요함 (1회 완전 충전으로 약 150km 주행 가능)
	수준 (4개)	① 휘발유 ② 경유 ③ 하이브리드(휘발유+전기) ④ 전기(배터리)
4. 차종	설명	**차종은 차량의 크기 등에 따라 SUV·RV, 경차·소형차, 준중형차·중형차, 대형차로 구분됨** - **SUV**는 Sports Utility Vehicle의 줄임말로, 기아 스포티지, 현대 투싼, 산타페 등의 차량이 포함되고, **RV**는 Recreational Vehicle의 줄임말로 기아의 카니발과 같은 다인 승합차가 포함됨 - **경차**는 기아 모닝, 레이, 쉐보레 스파크 등의 차량이 포함되며, **소형차**는 기아 프라이드, 현대 엑센트 등의 차량이 포함됨 - **준중형차**는 기아 K3. 현대 아반떼 등의 차량이 포함되며, **중형차**는 기아 K5, 현대 소나타와 같은 차량이 포함됨 - **대형차**는 기아 k9, 현대 에쿠스, 제네시스 등의 차량이 포함됨
	수준 (4개)	① SUV·RV ② 경차·소형차 ③ 준중형차·중형차 ④ 대형차
5. 주유/충전소 접근 용이성	설명	**주유/충전소 접근성은 소비자가 위치한 곳에서 주유/충전소까지의 평균 거리를 의미함**
	수준 (3개)	① 2km ② 10km ③ 20km

문11. 다음 제시한 4개의 자동차 유형 중, 선호 순위를 1위부터 4위까지 응답해 주십시오.

자동차 유형		유형 A	유형 B	유형 C	유형 D
질문 1	1. 연료 비용	200원/km (260,000원/월)	100원/km (130,000원/월)	200원/km (260,000원/월)	150원/km (195,000원/월)
	2. 차량 가격	6,000만원	3,000만원	1,500만원	6,000만원
	3. 연료 종류	전기	경유	하이브리드(휘발유+전기)	휘발유
	4. 차종	대형	경차·소형차	경차·소형차	경차·소형차
	5. 주유/충전소 접근성	2km	2km	2km	10km
선호 순위 응답란 → (1위부터 4위까지 응답)		☐ 위	☐ 위	☐ 위	☐ 위

자동차 유형		유형 A	유형 B	유형 C	유형 D
질문 2	1. 연료 비용	100원/km (130,000원/월)	200원/km (260,000원/월)	100원/km (130,000원/월)	100원/km (130,000원/월)
	2. 차량 가격	1,500만원	4,500만원	6,000만원	4,500만원
	3. 연료 종류	전기	경유	하이브리드(휘발유+전기)	휘발유
	4. 차종	준중형·중형	SUV·RV	SUV·RV	대형
	5. 주유/충전소 접근성	10km	10km	20km	2km
선호 순위 응답란 → (1위부터 4위까지 응답)		☐ 위	☐ 위	☐ 위	☐ 위

자동차 유형		유형 A	유형 B	유형 C	유형 D
질문 3	1. 연료 비용	50원/km (65,000원/월)	150원/km (195,000원/월)	150원/km (195,000원/월)	50원/km (65,000원/월)
	2. 차량 가격	4,500만원	1,500만원	4,500만원	1,500만원
	3. 연료 종류	전기	경유	하이브리드(휘발유+전기)	휘발유
	4. 차종	경차·소형차	대형	준중형·중형	SUV·RV
	5. 주유/충전소 접근성	20km	20km	2km	2km
선호 순위 응답란 → (1위부터 4위까지 응답)		☐ 위	☐ 위	☐ 위	☐ 위

자동차 유형		유형 A	유형 B	유형 C	유형 D
질문 4	1. 연료 비용	150원/km (195,000원/월)	50원/km (65,000원/월)	50원/km (65,000원/월)	200원/km (260,000원/월)
	2. 차량 가격	3,000만원	6,000만원	3,000만원	3,000만원
	3. 연료 종류	전기	경유	하이브리드(휘발유+전기)	휘발유
	4. 차종	SUV·RV	준중형·중형	대형	준중형·중형
	5. 주유/충전소 접근성	2km	2km	10km	20km
선호 순위 응답란 → (1위부터 4위까지 응답)		☐ 위	☐ 위	☐ 위	☐ 위

Appendix 4: Structural Similarities of Dummy in RRM and RUM

This section proves structural similarities of Dummy between RUM and RRM and explain why RUM and RRM did not classified in the Heterogeneous Choice Model for Respondent Decision Heuristics Strategy.

For a dummy attribute x_d, consider that a dummy attributes are existed, then the form of dummy attributes in RUM is shown in eq. (A4. 1). And for a dummy attribute x_d, if an individual choose an alternative *j*, in comparison with alternative *m*, the RRM for dummy attributes are shown in Eq. (A4. 2)

$$RUM_{dummy} = x_d \beta_d = \begin{cases} \beta_d & \text{if } x_d = 1 \\ 0 & o/w \end{cases} \qquad \text{Eq. (A4. 1)}$$

$$RRM_{dummy} = \log\left(1 + \exp\left(\beta_d \left(x_{md} - x_{jd}\right)\right)\right) \qquad \text{Eq. (A4. 2)}$$

In RUM cases, dummy attributes have simple formation, only remain utility coefficients. On contrary to this, RRM is different case by case. At first, if chosen alternatives have same values with non-chosen alternatives, then RRM structure draws log(2) and it is reduced into zero in the model, because if $x_{md} = x_{jd}$, then

none of regret and rejoice occurred. However, if the regret coefficient is positive, and non-chosen alternative had a dummy attributes but chosen had not, then the regret coefficient survived [Eq. (A4. 4)]. On the contrary to this, if the regret coefficient is positive and chosen alternative had a dummy attributes but non-chosen had not, then RRM diminishing to zero [Eq. (A4. 5)]. If the regret coefficient is negative, the structure is reversed.

$$case\ 1: WLOG,\ \beta_d \text{ is positive or negative, if } x_{md} = x_{jd}$$
$$RRM_{dummy,m\leftrightarrow j} = \log\left(1+\exp\left(\beta_d\left(x_{md}-x_{jd}\right)\right)\right) = \log(2) \simeq 0 \qquad \text{Eq. (A4. 3)}$$

$$case\ 1-1:\ \beta_d \geq 0 \text{ if } x_{md} = 1,\ x_{jd} = 0$$
$$RRM_{dummy,m\leftrightarrow j} = \log\left(1+\exp\left(\beta_d\right)\right) \simeq \beta_d \qquad \text{Eq. (A4. 4)}$$

$$case\ 1-2:\ \beta_d \geq 0 \text{ if } x_{md} = 0,\ x_{jd} = 1$$
$$RRM_{dummy,m\leftrightarrow j} = \log\left(1+\exp\left(-\beta_d\right)\right) \simeq 0 \qquad \text{Eq. (A4. 5)}$$

$$case\ 2-1:\ \beta_d < 0 \text{ if } x_{md} = 1,\ x_{jd} = 0$$
$$RRM_{dummy,m\leftrightarrow j} = \log\left(1+\exp\left(\beta_d\right)\right) \simeq 0 \qquad \text{Eq. (A4. 6)}$$

$$case\ 2-2:\ \beta_d < 0 \text{ if } x_{md} = 0,\ x_{jd} = 1$$
$$RRM_{dummy,m\leftrightarrow j} = \log\left(1+\exp\left(-\beta_d\right)\right) \simeq -\beta_d \qquad \text{Eq. (A4. 7)}$$

Assume that the choice situation suggests four alternatives (Alt1, Alt2, Alt3, Alt4), and it has a good property dummy attributes on it, (0, 0, 1, 1). If an individual *i* chooses Alt3, then RUM and RRM structure of individual *i* is shown

in Eq. (A4. 8). If an individual *i* chooses Alt1, then RUM and RRM structure of individual *i* is shown in Eq. (A4. 8).

$$
\begin{aligned}
&Case3-1: \beta_d \geq 0, \exists \left(\mathrm{Alt}_1, \mathrm{Alt}_2, \mathrm{Alt}_3, \mathrm{Alt}_4\right) \\
&\qquad x_d \rightarrow (0,0,1,1), \text{choosing } \mathrm{Alt}_3 \text{ or } \mathrm{Alt}_4 \\
&RUM_{dummy} = \beta_{d,RUM} \\
&RRM_{dummy} = \sum_{m \neq 3} \log\left(1+\exp\left(\beta_d\left(x_m - x_3\right)\right)\right) \\
&\qquad = \log\left(1+\exp\left(\beta_d\left(x_m - x_3\right)\right)\right) \simeq 0
\end{aligned}
\qquad \text{Eq. (A4. 8)}
$$

$$
\begin{aligned}
&Case3-2: \beta_d \geq 0, \exists \left(\mathrm{Alt}_1, \mathrm{Alt}_2, \mathrm{Alt}_3, \mathrm{Alt}_4\right) \\
&\qquad x_d \rightarrow (0,0,1,1), \text{choosing } \mathrm{Alt}_1 \text{ or } \mathrm{Alt}_2 \\
&RUM_{dummy} = 0 \\
&RRM_{dummy} = \sum_{m \neq 3} \log\left(1+\exp\left(\beta_d\left(x_m - x_3\right)\right)\right) \simeq 2\beta_{d,RRM}
\end{aligned}
\qquad \text{Eq. (A4. 9)}
$$

In the modified utility structure, the structure of Case 3-1 and Case 3-2 reduced to Eq. (A4.10). In any cases, only one parameters remained in the opposite

$Case3-1'$:

$MU_{dummy} = \tau_d \beta_{d,RUM} - (1-\tau_d)(0)$

$Case3-2'$:

$MU_{dummy} = \tau_d (0) - (1-\tau_d)(2\beta_{d,RRM})$

if RUM structure is selected,

if $\text{Alt}_{3 \text{ or } 4}$ is chosen, $\text{MU}_{dummy} = \beta_{d,RUM}$

if $\text{Alt}_{1 \text{ or } 2}$ is chosen, $\text{MU}_{dummy} = 0$

if RRM structure is selected,

if $\text{Alt}_{3 \text{ or } 4}$ is chosen, $\text{MU}_{dummy} = 0$

if $\text{Alt}_{1 \text{ or } 2}$ is chosen, $\text{MU}_{dummy} = -2\beta_{d,RRM}$

Eq. (A4. 10)

In these cases, no structural difference between RUM structure and RRM structure, excepts for the number of estimable beta, which the scale is also controlled in hierarchical structure. Therefore, it is hard to classify structures between RUM and RRM.

Appendix 5: Full Empirical results of Empirical studies (Chapter 4)

Table 46. Analysis Results of ZEH Choice behavior (HVSC, HVS, HB)

		HVSC Logit			HVS Logit			HB Logit		
		Mean		S.D.	Mean		S.D.	Mean		S.D.
	Major Firm	2.331	***	0.288	2.003	***	0.570	0.699	***	0.212
	Renewable	-0.158		0.137	-0.147		0.386	-0.099		0.136
	Mechanical Vent	-0.030		0.166	0.286		0.309	0.111		0.144
	Heat Exchange Vent	-0.680	***	0.208	-0.513	*	0.418	-0.300		0.259
	Access Time	-1.442	***	0.266	-1.365	***	0.356	-0.536	***	0.133
	CO2 Reduction	0.460	***	0.069	0.490	***	0.242	0.273	***	0.112
	Utility Cost Reduction	1.550	***	0.113	1.472	***	0.153	1.077	***	0.140
	Cost	-1.851	***	0.273	-1.435	***	0.364	-0.729	***	0.188
	No Choice	-3.314	***	0.350	-2.284	***	0.524	-1.494	***	0.396
Major Firm	Constant	-0.639	***	0.341	(Prob)					
	Seoul	1.540	***	0.225	0.361	***	0.089			
	APT	0.700	***	0.216						
	Home Owner	-1.795	***	0.525						
	Family	-0.118		0.120						
	Univ	0.127		0.199						
	Htech Perception	-0.349	***	0.135						
	Eco Perception	0.477		0.361						
	Heat Cost	0.267	**	0.099						
	Commute	-0.109	**	0.069						
	Homeprice>5	1.014	***	0.458						
Renewable	Constant	-0.145		0.381	(Prob)					
	Seoul	-0.068		0.379	0.405	***	0.086			

	APT	0.723	***	0.271			
	Home Owner	-1.375	**	0.539			
	Family	0.766	***	0.219			
	Univ	0.440	*	0.221			
	Htech Perception	-0.631	***	0.180			
	Eco Perception	0.211	*	0.259			
	Heat Cost	0.020		0.328			
	Commute	-0.485	*	0.261			
	Homeprice>5	-0.395	*	0.354			
Vent Type	Constant	0.729	**	0.361	(Prob)		
	Seoul	-0.344		0.360	0.391	***	0.222
	APT	-1.635	**	0.693			
	Home Owner	0.342		0.544			
	Family	-0.561	***	0.091			
	Univ	0.101		0.348			
	Htech Perception	0.638	**	0.240			
	Eco Perception	-0.381	***	0.081			
	Heat Cost	0.034		0.137			
	Commute	0.004		0.123			
	Homeprice>5	-0.253		0.268			
Access Time	Constant	0.081		0.725	(Prob)		
	Seoul	-1.168	***	0.152	0.385	***	0.140
	APT	0.180		0.278			
	Home Owner	-0.152		0.414			
	Family	0.332	**	0.148			
	Univ	-0.775	***	0.276			
	Htech Perception	-0.399	***	0.084			
	Eco Perception	0.644	***	0.140			
	Heat Cost	-0.209		0.172			
	Commute	0.494	***	0.100			
	Homeprice>5	-0.274		0.449			

CO2 Reduction	Constant	-0.910	**	0.356	(Prob)		
	Seoul	1.669	***	0.330	0.465	***	0.170
	APT	0.621	***	0.206			
	Home Owner	-0.207		0.503			
	Family	-0.750	*	0.459			
	Univ	-0.203		0.339			
	Htech Perception	0.413	***	0.183			
	Eco Perception	-0.132		0.235			
	Heat Cost	0.365	***	0.113			
	Commute	-0.101		0.105			
	Homeprice>5	-1.283	***	0.238			
Utility Cost Reduction	Constant	0.914	*	0.536	(Prob)		
	Seoul	1.028	***	0.277	0.727	***	0.070
	APT	0.184		0.233			
	Home Owner	-0.884	**	0.376			
	Family	0.427	***	0.179			
	Univ	-0.378		0.327			
	Htech Perception	0.535	***	0.172			
	Eco Perception	-0.490	***	0.198			
	Heat Cost	-0.080		0.095			
	Commute	-0.112	*	0.134			
	Homeprice>5	0.972	**	0.346			
Cost	Constant	0.827	**	0.312	(Prob)		
	Seoul	-0.670	***	0.229	0.624	***	0.052
	APT	-0.651	**	0.240			
	Home Owner	0.304	*	0.277			
	Family	0.363	***	0.111			
	Univ	0.012		0.207			
	Htech Perception	0.007		0.106			
	Eco Perception	-0.854	***	0.125			
	Heat Cost	-0.974	***	0.118			

	Commute	-0.093		0.184						
	Homeprice>5	-0.475		0.376						
No Choice	Constant	-1.707	***	0.510	(Prob)					
	Seoul	2.199	***	0.526	0.683	***	0.089			
	APT	1.085	***	0.470						
	Home Owner	0.707	*	0.420						
	Family	0.221	**	0.104						
	Univ	0.284	*	0.170						
	Htech Perception	0.165	*	0.146						
	Eco Perception	-0.497	***	0.175						
	Heat Cost	0.660	***	0.153						
	Commute	-0.012		0.080						
	Homeprice>5	-0.621		0.541						
	Sigma_0_0	2.696	***	0.948	4.577	***	2.894	2.479	***	0.748
	Sigma_0_1	-0.008		0.197	0.221		0.524	-0.102		0.246
	Sigma_0_2	-0.128		0.216	-0.013		0.302	0.102		0.167
	Sigma_0_3	-0.083		0.299	0.038		0.456	0.036		0.173
	Sigma_0_4	-0.087		0.236	-0.022		0.428	-0.033		0.207
	Sigma_0_5	0.087		0.137	0.053		0.296	0.031		0.111
	Sigma_0_6	-0.039		0.312	0.029		0.420	0.281		0.258
	Sigma_0_7	-0.075		0.893	2.706	*	2.074	0.212		0.576
	Sigma_0_8	1.307	*	0.879	0.652		2.903	-1.629	*	1.149
	Sigma_1_1	0.196	***	0.349	0.907	***	0.623	0.662	***	0.216
	Sigma_1_2	-0.020		0.067	-0.054		0.139	-0.140	*	0.119
	Sigma_1_3	0.001		0.055	0.030		0.161	0.049		0.087
	Sigma_1_4	-0.012		0.060	-0.004		0.152	-0.054		0.129
	Sigma_1_5	0.004		0.037	0.010		0.141	0.020		0.049
	Sigma_1_6	0.032		0.066	0.082		0.203	0.097		0.121
	Sigma_1_7	-0.177		0.337	0.580		1.093	0.298		0.322
	Sigma_1_8	0.363		0.675	2.014	*	1.511	0.935	**	0.590
	Sigma_2_2	0.354	***	0.286	0.322	***	0.547	0.211	***	0.163

Sigma_2_3	-0.080		0.093	0.009		0.154	-0.006		0.057
Sigma_2_4	0.052		0.096	0.010		0.097	0.054		0.103
Sigma_2_5	-0.015		0.035	-0.024		0.115	-0.010		0.033
Sigma_2_6	0.049		0.062	-0.030		0.110	-0.078		0.097
Sigma_2_7	-0.522		0.661	-0.201		0.643	-0.102		0.226
Sigma_2_8	-0.487		0.433	-0.444		0.860	-0.475		0.466
Sigma_3_3	0.600	***	0.480	0.407	***	0.597	0.191	***	0.219
Sigma_3_4	0.037		0.086	0.017		0.130	0.018		0.074
Sigma_3_5	0.097		0.094	0.004		0.080	0.012		0.041
Sigma_3_6	0.016		0.067	0.003		0.158	-0.046		0.098
Sigma_3_7	-0.090		0.438	-0.022		0.781	0.019		0.225
Sigma_3_8	0.468		0.490	0.167		0.841	0.285		0.507
Sigma_4_4	0.229	***	0.231	0.390	***	0.678	0.269	***	0.313
Sigma_4_5	0.021		0.051	-0.007		0.090	0.016		0.056
Sigma_4_6	0.008		0.068	-0.017		0.150	-0.042		0.130
Sigma_4_7	0.135		0.470	0.055		0.711	0.240		0.373
Sigma_4_8	0.201		0.361	-0.202		0.902	0.124		0.527
Sigma_5_5	0.171	***	0.108	0.251	***	0.345	0.070	***	0.077
Sigma_5_6	-0.012		0.050	0.007		0.124	0.007		0.064
Sigma_5_7	0.144		0.261	0.332		0.660	0.054		0.158
Sigma_5_8	0.349	*	0.336	0.384		0.657	-0.034		0.264
Sigma_6_6	0.541	***	0.291	0.586	***	0.309	0.931	***	0.260
Sigma_6_7	-0.833	**	0.473	-1.032		0.848	-0.463		0.365
Sigma_6_8	0.241		0.559	0.682		0.982	0.114		0.581
Sigma_7_7	14.755	***	2.982	17.047	***	4.646	5.798	***	1.046
Sigma_7_8	1.090		1.952	4.368		4.117	0.232		1.228
Sigma_8_8	8.659	***	3.325	26.686	***	11.052	16.258	***	3.994
bprecision	12.913	***	0.917						
Choicelogp	-1678.0	***	45.7	-1613.2	***	50.6	-1655.3	***	58.3

Table 47. Analysis Results of Zero Energy House Choice behavior (HDH Cov RUM-RRM, HDH RUM-RRM, RRM, RUM)

	HDH RUM-RRM w/ Cov.			HDH RUM-RRM			RRM			RUM		
Variables	Mean		S.D.	Mean		S.D.	Mean		S.D.	Mean		S.D.
(Dummy)												
Brand	0.511	***	0.153	0.503	***	0.213	-0.157		0.147	0.699	***	0.218
Renewable	-0.305	***	0.093	-0.222	**	0.119	-0.701	***	0.084	-0.098		0.131
Mechanical Vent	-0.240	**	0.162	-0.106		0.152	-0.874	***	0.102	0.098		0.148
Heat Recovery Vent	-0.760	***	0.225	-0.641	***	0.246	-2.102	***	0.161	-0.310		0.257
No Choice	-1.262	***	0.332	-1.373	***	0.424	-1.071	***	0.398	-1.483	***	0.366
(RUM)												
Access Time	-1.072	***	0.269	-1.274	***	0.503				-0.522	***	0.141
Reduce CO2	-0.072		0.243	-0.076		0.230				0.263	***	0.117
Utility Cost Reduction	1.326	***	0.186	1.308	***	0.262				1.063	***	0.143
Cost	-0.294	*	0.236	-1.255	***	0.365				-0.719	***	0.197
(RRM)												
Access Time	0.437	**	0.206	0.135		0.304	-0.546	***	0.131			
CO2	-0.263		0.269	0.008		0.534	0.911	***	0.086			
Utility Cost Reduction	0.151		0.165	0.236		0.286	-0.523	**	0.129			
Cost	-0.353		0.773	0.847	*	0.636	0.095		0.191			
(Access Time)				P(Access Time)								
Seoul	-2.449	***	0.444	0.421	***	0.177						
APT	0.043		0.415									
Home Owner	0.316		0.391									
Family	0.032		0.203									
Hightech Perception	-0.305	**	0.157									
Eco perception	0.471	*	0.250									
Commute	0.278	***	0.097									
Heatcost	-0.307	***	0.128									

(Reduce CO2)					P(Reduce CO2)							
Seoul	-0.034		0.325	0.783	***	0.101						
APT	-0.581		0.730									
Home Owner	-0.396		0.648									
Family	-0.195		0.294									
Hightech Perception	0.221		0.233									
Eco perception	-0.342		0.399									
Commute	0.180		0.233									
Heatcost	-0.022		0.401									
Utility Cost Reduction				P(Utility Cost Reduction)								
Seoul	0.441		0.404	0.638	***	0.124						
APT	0.006		0.256									
Home Owner	0.228		0.269									
Family	0.703	***	0.276									
Hightech Perception	0.258	*	0.141									
Eco perception	-0.092		0.220									
Commute	-0.063		0.310									
Heatcost	0.176		0.179									
(Cost)					P(Cost)							
Seoul	1.343	***	0.253	0.675	***	0.068						
APT	0.812	***	0.156									
Home Owner	0.060		0.279									
Family	-0.179		0.174									
Hightech Perception	0.465	***	0.185									
Eco perception	-0.217	**	0.145									
Commute	-0.093		0.097									
Heatcost	0.301	**	0.144									
Choicelogp	-1574	***	51.806	-1571	***	60.697	-1919	***	48.431	-1662	***	57.342
bprecision	9.406	***	0.527									
Sigma__0_0	2.046	***	0.672	2.070	***	0.705	2.238	***	0.733	2.351	***	0.710
Sigma__0_1	0.068		0.121	0.044		0.112	-0.056		0.120	0.111		0.169

Sigma__0_2	0.144		0.183	0.030		0.152	-0.057		0.183	0.012		0.152
Sigma__0_3	-0.014		0.156	-0.042		0.145	0.010		0.284	-0.038		0.211
Sigma__0_4	-0.512		0.795	-0.658		1.182	-4.013	***	1.276	-1.410	*	1.064
Sigma__0_5	-0.228		0.234	-0.006		0.335	-0.552	***	0.186	-0.126		0.217
Sigma__0_6	-0.004		0.179	0.002		0.093	0.060		0.096	0.017		0.100
Sigma__0_7	-0.168		0.260	0.046		0.316	0.851	***	0.210	0.281		0.243
Sigma__0_8	0.409		0.544	0.905		0.954	0.123		0.198	0.274		0.591
Sigma__0_9	-0.005		0.072	0.008		0.109						
Sigma__0_10	-0.033		0.130	0.041		0.514						
Sigma__0_11	0.006		0.077	0.001		0.108						
Sigma__0_12	-1.788		2.499	0.038		0.237						
Sigma__1_1	0.140	***	0.123	0.133	***	0.140	0.106	***	0.099	0.218	***	0.166
Sigma__1_2	-0.008		0.048	0.003		0.038	0.024		0.050	-0.009		0.054
Sigma__1_3	0.006		0.041	0.008		0.044	0.131	*	0.144	0.030		0.072
Sigma__1_4	-0.264	*	0.231	-0.163		0.360	0.293		0.421	-0.422		0.450
Sigma__1_5	-0.072		0.076	-0.057		0.110	-0.051		0.069	-0.150	**	0.112
Sigma__1_6	-0.016		0.058	-0.007		0.022	-0.001		0.016	-0.011		0.032
Sigma__1_7	-0.048		0.103	-0.028		0.085	-0.007		0.067	-0.076		0.101
Sigma__1_8	-0.083		0.227	-0.003		0.314	-0.004		0.033	-0.118		0.244
Sigma__1_9	-0.006		0.018	-0.006		0.026						
Sigma__1_10	-0.023		0.038	-0.015		0.128						
Sigma__1_11	-0.007		0.021	-0.008		0.032						
Sigma__1_12	-0.146		0.582	-0.001		0.064						
Sigma__2_2	0.518	***	0.326	0.240	***	0.263	0.322	***	0.214	0.152	***	0.176
Sigma__2_3	0.030		0.091	0.007		0.052	0.251	*	0.208	0.014		0.064
Sigma__2_4	0.175		0.422	0.306		0.501	1.300	**	0.931	0.261		0.546
Sigma__2_5	0.027		0.152	0.020		0.120	0.204	**	0.142	0.032		0.080
Sigma__2_6	0.121		0.134	0.009		0.034	-0.017		0.036	0.011		0.034
Sigma__2_7	-0.145		0.174	-0.035		0.126	-0.070		0.097	-0.041		0.091
Sigma__2_8	-0.054		0.310	0.058		0.418	0.017		0.058	0.156		0.230
Sigma__2_9	0.007		0.040	0.005		0.040						

Sigma__2_10	0.012		0.052	-0.001		0.200						
Sigma__2_11	0.013		0.045	0.007		0.053						
Sigma__2_12	0.338		0.889	0.006		0.095						
Sigma__3_3	0.269	***	0.279	0.196	***	0.242	1.147	***	0.488	0.244	***	0.295
Sigma__3_4	0.267		0.334	0.193		0.557	2.194	**	1.238	0.046		0.571
Sigma__3_5	0.003		0.090	0.005		0.109	0.099		0.205	-0.029		0.115
Sigma__3_6	0.047		0.097	0.011		0.042	-0.006		0.049	0.017		0.053
Sigma__3_7	-0.044		0.128	-0.025		0.121	0.098		0.177	-0.027		0.117
Sigma__3_8	0.251		0.369	0.191		0.381	0.015		0.097	0.263		0.371
Sigma__3_9	-0.011		0.028	0.010		0.039						
Sigma__3_10	0.006		0.034	-0.006		0.160						
Sigma__3_11	-0.003		0.028	0.001		0.038						
Sigma__3_12	0.251		0.804	0.001		0.069						
Sigma__4_4	11.049	***	2.722	18.179	***	4.945	25.752	***	5.656	16.061	***	4.057
Sigma__4_5	1.051	**	0.818	1.215		1.118	1.874	***	0.927	0.936	**	0.630
Sigma__4_6	0.279		0.508	0.113		0.266	-0.163		0.258	0.010		0.249
Sigma__4_7	0.414		0.674	0.662		0.953	-1.707	**	0.796	0.120		0.596
Sigma__4_8	4.436	***	1.472	2.807		2.667	-0.051		0.487	0.236		1.173
Sigma__4_9	0.133		0.203	0.019		0.304						
Sigma__4_10	0.223		0.283	0.503		1.621						
Sigma__4_11	0.077		0.204	0.030		0.342						
Sigma__4_12	4.662	*	4.595	0.136		0.752						
Sigma__5_5	0.772	***	0.439	1.003	***	0.766	0.779	***	0.279	0.652	***	0.202
Sigma__5_6	0.041		0.127	0.010		0.067	-0.025		0.049	0.019		0.050
Sigma__5_7	0.124		0.218	0.151		0.274	-0.398	***	0.189	0.071		0.117
Sigma__5_8	-0.316		0.500	0.149		0.772	-0.044		0.083	0.280		0.279
Sigma__5_9	0.025		0.058	0.008		0.077						
Sigma__5_10	0.016		0.066	0.020		0.394						
Sigma__5_11	0.010		0.061	-0.006		0.070						
Sigma__5_12	0.429		1.105	0.004		0.173						
Sigma__6_6	0.377	***	0.308	0.080	***	0.084	0.032	***	0.041	0.067	***	0.073

Sigma__6_7	-0.036		0.201	0.012		0.076	0.012		0.034	0.018		0.061
Sigma__6_8	0.119		0.459	0.016		0.259	-0.001		0.015	0.081		0.162
Sigma__6_9	-0.012		0.044	-0.004		0.023						
Sigma__6_10	0.020		0.052	-0.007		0.100						
Sigma__6_11	-0.006		0.043	-0.005		0.023						
Sigma__6_12	-0.397		0.847	0.000		0.048						
Sigma__7_7	1.283	***	0.492	1.266	***	0.638	0.712	***	0.211	0.934	***	0.263
Sigma__7_8	-0.748	*	0.542	-1.119		0.991	0.037		0.095	-0.449	*	0.337
Sigma__7_9	-0.005		0.056	-0.005		0.084						
Sigma__7_10	-0.015		0.090	0.059		0.406						
Sigma__7_11	0.019		0.074	0.016		0.091						
Sigma__7_12	0.143		1.259	-0.005		0.180						
Sigma__8_8	8.289	***	1.526	14.029	***	4.857	0.154	***	0.237	5.678	***	1.050
Sigma__8_9	-0.031		0.189	-0.070		0.356						
Sigma__8_10	-0.079		0.200	-0.097		1.301						
Sigma__8_11	-0.090		0.189	0.015		0.330						
Sigma__8_12	1.050		4.325	-0.051		0.620						
Sigma__9_9	0.055	***	0.060	0.096	***	0.124						
Sigma__9_10	0.001		0.017	-0.021		0.121						
Sigma__9_11	-0.006		0.021	-0.005		0.024						
Sigma__9_12	0.147		0.298	-0.002		0.056						
Sigma__10_10	0.103	***	0.102	2.420	***	3.446						
Sigma__10_11	0.001		0.019	-0.017		0.128						
Sigma__10_12	0.176		0.357	0.014		0.243						
Sigma__11_11	0.063	***	0.065	0.118	***	0.108						
Sigma__11_12	0.001		0.331	-0.001		0.067						
Sigma__12_12	35.398	***	32.109	0.543	***	0.676						

Table 48. Analysis Results of TBC (HVSC, HVS, HB)

		HVSC Logit			HVS Logit			HB Logit		
		Mean		S.D.	Mean		S.D.	Mean		S.D.
Mobile Carrier	KT	1.312	**	0.578	0.632		0.703	0.720	***	0.341
	LGU+	1.025	**	0.454	-0.026		0.643	0.512	**	0.288
	Period	-0.425	***	0.108	-0.630	***	0.193	-0.259	**	0.122
	Discount Mobile	0.984	***	0.186	1.174	***	0.294	0.479	***	0.138
	Discount Pay-TV	1.681	***	0.187	1.640	***	0.282	0.854	***	0.179
	Choicelogp	-2891.1		94.2	-2897.7		100.3	-3101.0		97.1
Mobile Carrier	Constant	-0.336		0.664	P(Mob Carrier)					
	Age	-0.194		0.168	0.466	***	0.103			
	Male	0.005		0.272						
	Decision	-1.074	***	0.485						
	Bundle Mobile	0.946	***	0.335						
	Installment	-0.002		0.578						
	Phone bill	0.177		0.176						
	Income	-0.050		0.148						
	Edu	-0.223		0.175						
	Change w/i 6yr	0.747	**	0.433						
Period	Constant	-0.797		0.887	P(Period)					
	Age	0.236		0.210	0.637	***	0.133			
	Male	0.083		0.377						
	Decision	0.563		0.644						
	Bundle Mobile	0.145		0.435						
	Installment	0.104		0.524						
	Phone bill	-0.341		0.240						
	Income	0.398	**	0.209						
	Edu	0.142		0.274						
	Change w/i 6yr	1.262	***	0.455						
Discount Mobile	Constant	1.007	**	0.521	P(D_Mob)					
	Age	0.185		0.179	0.723	***	0.080			

	Male	-0.032		0.377						
	Decision	-0.772	*	0.432						
	Bundle Mobile	0.026		0.428						
	Installment	0.617	*	0.412						
	Phone bill	-0.099		0.208						
	Income	-0.190		0.159						
	Edu	0.087		0.164						
	Change w/i 6yr	0.137		0.309						
Discount Pay-TV	Constant	-0.915	**	0.371	P(D_Pay-TV)					
	Age	-0.103		0.133	0.750	***	0.073			
	Male	-0.281		0.275						
	Decision	0.271		0.327						
	Bundle Mobile	0.501	**	0.259						
	Installment	0.956	***	0.356						
	Phone bill	-0.088		0.164						
	Income	0.172		0.137						
	Edu	-0.386	***	0.153						
	Change w/i 6yr	1.042	***	0.275						
	Sigma_0_0	56.026	***	15.613	41.323	***	20.769	9.433	***	1.674
	Sigma_0_1	17.806	***	5.733	13.708	***	6.137	4.146	***	1.215
	Sigma_0_2	6.470	***	2.031	2.382	*	1.621	0.631	**	0.413
	Sigma_0_3	-0.612		2.758	-4.177	**	2.478	-0.359		0.414
	Sigma_0_4	-9.905	***	3.632	-1.663		2.205	-0.610		0.531
	Sigma_1_1	23.880	***	10.413	35.941	***	31.014	4.907	***	1.293
	Sigma_1_2	2.061	*	1.445	0.966		1.527	0.502	*	0.456
	Sigma_1_3	-3.250	**	2.306	-6.397	***	2.594	-1.315	***	0.392
	Sigma_1_4	0.224		2.498	4.856	***	3.042	0.813	**	0.381
	Sigma_2_2	1.464	***	0.395	0.849	***	0.347	0.554	***	0.223
	Sigma_2_3	-0.372		0.509	-0.774	**	0.487	-0.139		0.129
	Sigma_2_4	-1.887	***	0.611	-0.491		0.476	0.003		0.148
	Sigma_3_3	2.689	***	0.765	3.530	***	0.847	1.723	***	0.280

Sigma_3_4	-0.301		0.553	-0.198		0.577	-0.544	***	0.195
Sigma_4_4	4.269	***	0.984	2.504	***	0.695	1.344	***	0.277

Table 49. Analysis Results of TBC (HDH Cov RUM-RRM, HDH RUM-RRM, RRM, RUM)

	HDH Cov. RUM-RRM			HDH RUM-RRM			RRM			RUM		
	Mean		S.D.	Mean		S.D.	Mean		S.D.	Mean		S.D.
(Dummy)												
KT	0.479	*	0.297	0.329		0.333	2.252	***	0.162	0.570	*	0.307
LGU+	0.151		0.225	0.072		0.239	0.494	***	0.116	0.336		0.301
(RUM)												
Period	-0.528	***	0.165	-0.805	***	0.198				-0.336	***	0.128
Discount_Mobile	1.995	***	0.372	0.695	***	0.244				0.527	***	0.127
Discount_Pay-TV	1.376	***	0.160	1.205	***	0.211				0.952	***	0.165
(RRM)												
Period	-0.223		0.254	-0.069		0.241	-0.247	***	0.074			
Discount_Mobile	-0.102		0.187	0.390		0.603	-0.659	***	0.122			
Discount_Pay-TV	0.559	**	0.278	0.583	**	0.495	0.785	***	0.089			
(Period)				P(RUM, Period)								
Decision	-0.287		0.298	.553	***	0.209						
Bundle-Mob	0.278		0.346									
Phone Bill	-0.220		0.181									
Income	0.236		0.265									
Edu	0.236		0.258									
Change	0.980	***	0.460									
(Discount_Mob)				P(RUM, D_Mob)								
Decision	-1.397	***	0.390	0.673	***	0.188						
Bundle-Mob	-0.290		0.316									

Phone Bill	0.323	*	0.177									
Income	-0.170		0.182									
Edu	0.040		0.175									
Change	0.209		0.237									
(Discount_Pay-TV)				P(RUM, D_Pay-TV)								
Decision	0.414	*	0.278	0.839	***	0.079						
Bundle-Mob	0.459	*	0.295									
Phone Bill	0.112		0.186									
Income	0.110		0.107									
Edu	0.031		0.201									
Change	1.414	***	0.279									
Choicelogp	-2874.9		101.9	-2941.4		145.3	-3457.4		79.8	-3110.6		95.5
Sigma_0_0	10.354	***	1.727	10.024	***	1.879	4.812	***	0.891	9.286	***	1.641
Sigma_0_1	4.709	***	1.171	4.406	***	1.253	3.997	***	0.704	3.819	***	1.140
Sigma_0_2	1.410	***	0.745	0.572	*	0.516	1.192	***	0.280	0.465	*	0.384
Sigma_0_3	-0.683		1.243	-1.532	**	1.203	-0.941	**	0.462	-0.469		0.419
Sigma_0_4	-1.524	**	0.648	-1.474	**	0.849	0.138		0.295	-0.565		0.483
Sigma_0_5	0.024		0.571	-0.037		0.370						
Sigma_0_6	-0.904	*	0.616	0.196		2.362						
Sigma_0_7	-0.560		1.155	-0.222		0.646						
Sigma_1_1	6.335	***	1.508	5.607	***	1.573	6.490	***	0.944	4.455	***	1.236
Sigma_1_2	1.540	***	0.797	0.738		0.704	2.639	***	0.363	0.285		0.411
Sigma_1_3	0.053		0.759	-1.745	***	0.660	-3.747	***	0.485	-1.389	***	0.345
Sigma_1_4	1.565	***	0.436	1.455	***	0.686	1.283	***	0.242	0.928	**	0.367
Sigma_1_5	0.919	*	0.775	0.207		0.417						
Sigma_1_6	-2.868	***	0.700	-2.877	*	2.004						
Sigma_1_7	1.421	*	1.025	0.124		0.521						
Sigma_2_2	1.040	***	0.517	0.476	***	0.374	1.669	***	0.249	0.456	***	0.204
Sigma_2_3	-0.621		0.691	-0.388		0.394	-2.455	***	0.310	-0.173		0.140
Sigma_2_4	0.372		0.330	0.219		0.375	0.969	***	0.147	0.068		0.125
Sigma_2_5	0.296	*	0.250	0.021		0.090						

Sigma_2_6	-1.040	***	0.378	-0.470		0.734						
Sigma_2_7	0.486		0.432	0.062		0.240						
Sigma_3_3	3.068	***	2.762	1.998	***	0.565	4.334	***	0.570	1.808	***	0.244
Sigma_3_4	0.600		0.842	-0.755	*	0.490	-1.771	***	0.320	-0.472	**	0.200
Sigma_3_5	-0.233		0.429	-0.193		0.323						
Sigma_3_6	-0.033		0.509	0.992		1.300						
Sigma_3_7	0.107		0.764	-0.106		0.431						
Sigma_4_4	3.106	***	0.602	2.893	***	0.936	0.872	***	0.193	1.359	***	0.275
Sigma_4_5	0.618		0.577	0.170		0.280						
Sigma_4_6	-2.170	***	0.592	-2.641		2.045						
Sigma_4_7	1.077	*	0.791	0.207		0.418						
Sigma_5_5	0.727	***	0.558	0.194	***	0.293						
Sigma_5_6	-0.822	*	0.670	-0.241		0.662						
Sigma_5_7	0.270		0.334	-0.001		0.109						
Sigma_6_6	2.877	***	0.777	8.980	***	9.724						
Sigma_6_7	-1.243	*	0.806	-0.296		0.691						
Sigma_7_7	2.282	***	1.191	0.755	***	1.139						
bprecision	8.516	***	1.034									

Abstract (Korean)

소비자의 이질성은 오랜 기간 동안 통계적 마케팅 선택모형 연구의 핵심적인 부분이었다. 소비자 이질성을 도출하기 위하여 다양한 확률적 접근방법들이(distributional approaches) 존재했고, 소비자 선호에 분포을 부여하여 소비자의 취향 이질성을 도출을 통해 소비자 이질성을 도출하는 방법론들이 제시되어 왔다. 본 연구는 소비자의 의사결정 전략을 확률적 변수 선택 모형 (Stochastic Search Variable Selection) 을 이용하여 포착하는 방법론을 제시한다. 제안하는 첫 번째 모형은 소비자의 대안 선택 시의 속성 비집중 (Attribute Non-Attendance) 행태를 소비자의 특성을 통하여 설명하는 모형이다. 소비자들은 복잡한 의사결정 상황에서 제공되는 모든 정보를 이용하지 못하고 의사결정 결과를 도출하게 된다. 선행 연구에서는 이러한 행태를 속성 비집중 이라는 용어로 설명하고 있고, 이에 대한 분석을 직접 응답자에게 묻거나, 고려대상이 되는 부분정보집합을 통계적으로 추론하는 방법론을 이용한다. 하지만 이러한 모형들은 개개인의 특성과 변수선택간의 관계를 소비자 특성과 연관 지어 설명하지 못한다. 본 연구에서 제안하고자 하는 모형은 소비자들의 attribute non-attendance 행태를 소비자의 특성과 연관 지어 설명할 수 있는 모형을 제시하고자 한다. 두 번째 모형은 소비자의 이질적인 의사결정구조를 효용 최대화(Random

Utility Maximization)와 후회 최소화(Random Regret Minimization)의 관점에서 설명하는 모형이다. 기존 연구는 소비자의 대안적 휴리스틱 의사결정 모형을 결정하기 위하여 AIC, BIC와 같은 모형추정적합도를 비교를 하여 소비자의 대안적 휴리스틱 의사결정 모형을 설명했다. 본 연구는 소비자의 개별적 의사결정 행태의 이질성을 효용 최대화와 후회 최소화 관점에서 베이지안 변수탐색 모형을 이용하여 분석하는 방법론을 제시하고자 한다.

실증분석은 제로에너지 하우스 선택 상황, 방송통신 결합상품 선택 상황, 그리고 차량 구매 상황의 세 가지 첨단기술 내구재에 대한 소비자 선호 분석을 이용하였다. 소비재와는 달리 첨단 기술 내구재의 선택에 있어 소비자는 많은 정보를 처리해야 하고, 소비자의 특정 선호에 대한 확실한 개인 선호가 반영되기 때문이다. 또한 소비자는 내구재 선택에 있어 복잡한 의사결정 상황에 마주하고 있기 때문에 다양한 의사결정 구조 이질성을 가지고 있기 때문이다. 실증 분석 결과는 이러한 소비자의 복합적 의사결정 구조와 특정 대안에 대한 고려를 잘 보여주고 있다.

본 연구에서 제안한 모형은 두 가지 함의가 있다. 첫번째로 제품생산단계에서 제품기획단계의 생산자는 소비자의 제품 특성 고려에 대한 이질성을 도출하는 것을 필요로 한다. 두 번째로, 시장세분화, 표적시장 선점, 위상정립 마케팅 (STP Marketing) 측면에서 소비자들의 특성에 따라 확실한 시장 세분화를 필요로 한다. 본 연구에서 제안하는 모형은 이러한 문제들을 해결할 수 있는 모형이다.

주요어: 이산선택모형; 이질적 의사결정 휴리스틱 모형; 속성 비집중 모형; 후회최소화 모형; 베이지안 추론; 확률적 변수 탐색 모형

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