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Benefit-scale model in Discrete Choice Model:

Bayesian learning approach on benefit scale parameter

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Abstract

Benefit-scale model in Discrete Choice Model:

Bayesian learning approach on benefit scale parameter

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This study proposes a benefit-scale model that introduces the scale parameter to the benefit-based model. The benefit-scale model has the advantage of being able to use data more effectively in discrete choice experiments when information is sparse. In this study, we show a method of extracting and implementing decision importance information based on the Bayesian learning method. The proposed benefit scale model shows better model fit, predictive power, and convergence in assignment probabilities than the standard multinomial logit and benefit-based model and provides different interpretations.

The indexed benefit-scale model, which is an applied model of the benefit-scale approach, showed no improvement in model fit compared to the standard model. This indicates that a careful approach is required when the researcher assumes that attributes are assigned to benefits, and that assignment probability is indeed heterogeneous. In addition, the possibility of capturing the heterogeneity in scale was tested and confirmed by including demographic variables in the scale parameter. It was also shown in this study that satiation can take place in both benefit level and utility-as-a-whole level.

For empirical validation of the model, Over-the-top(OTT) service data and alternative fuel vehicle data were used. This study provides service planning implications for IPTV or cable TV service operators and product planning implications for electric vehicle manufacturers.

Keywords: Discrete Choice Model; Integration Rule; Benefit-based Conjoint; Diminishing Marginal Utility; Scale parameter; Bayesian Learning

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Chapter 1. Introduction

1.1 Research background

Discrete choice experiment(DCE) based on random utility theory analyzes individual choices and preferences under the assumption that the utility from choice is composed of independent and linear part-worth of each attributes (McFadden & Train, 2000; Leong & Hensher, 2012, Chorus, 2014). Such discrete choice model(DCM) is known as a useful and effective method for analyzing the preferences of decision makers, and has developed in various fields; including products, services and national policies (Ahn et al., 2013; Cho et al., 2015; Choi et al., 2012; Kim et al., 2016; Kim et al., 2019).

In DCE design, an efficient design method such as a fractional factorial design method is used, so the linear additive assumption of utility is hardly a problem. However, there exists certain circumstances when the assumption that the utility of properties is linear additive may not be valid (Louviere, 1988; Kim et al., 2017).

This study focused on the method of integrating the utility between attributes in DCE in a sub-additive manner that considers satiation within attributes. Specifically, the satiation structure in utility assumes sub-additive integration within the same benefit nest. The model of Kim et al. (2017) using a nested satiation structure that assumes that the utility equation follows the law of diminishing marginal utility within the same benefit was extended in this study.

Among integration rule, I introduce two benefit formation approaches in Chapter 2. The method of utilizing the latent structure (Dellaert, 2018) and the method of using assignment probability (Kim et al., 2017). Using latent structure which priori defines the relationship between benefits and attributes is based on behavioral economic intuitions and therefore provides a richer interpretation. However, there is a limitation to this approach that abundant literatures that prove the priori structured relationship must be supported as relationship between decision makers' choice and benefit formation is not actually observed (Dellaert, 2018).

Key insight of benefit-based approach by Kim et al.(2017) is that identification of the attribute to benefit grouping requires only DCE choice data and does not require other structured questionnaires to use priori defined latent structure as in other benefit formation literatures[1]. A benefit-based approach also offers advantage that it can identify attributes that do not result in satiation of utility. This is particularly important when designing products, services, and policies composed of multiple attributes as the design can be cost-effectively improved by identifying attributes which satiation does not occur.

Also, benefit-based model employ more than twenty choice tasks (and also generated data). Twenty choice tasks are conventional number conjoint analysis but there are number of researches with less than eight choice task. If a small number of choice tasks can effectively summarize large amounts of information in DCE data, benefit-based model can be applied more universally.

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[1] See Arentze et al. (2015); Dellaert et al. (2018)

1.2 Research objective

I consider benefit-based model estimation method, in which Kim et al.(2017) used; and additional step in Bayesian estimation, which makes use of Bayesian learning of decision importance as scale parameter with MCMC simultaneously. In brief, I find that the information that benefit-scale model extracts from choice data is indeed important and leads to superior model fit, predictive power and enhances assignment probability convergence.

1.3 Research outline

The composition of this dissertation is as follows. Chapter 2 presents previous studies related to the model. In Chapter 3, the benefit-based model of Kim et al. (2017), the benefit-scale model of this study, and models extended from these models are presented. Chapter 4 presents the results of empirical analysis with two datasets using these two models, and Chapter 5 presents conclusions and limitations.

Chapter 2. Literature Review

In section 2.1, the general rules that consist discrete choice model, which is widely used econometric methodology for analyzing the preferences of decision makers is discussed. Section 2.2 discusses satiation properties in different dimensions, then Section 2.3 discusses approaches from factor analysis.

2.1 Choice Theories and Models

Discrete choice experiment(DCE) is an experimental method that reproduces situations similar to actual selections in order to elaborately grasp individual preferences for products and services (Green & Srinivasan, 1978). DCE is widely used in quantitative analysis of individual preferences in diverse fields (Ahn et al., 2013; Cho et al., 2015; Choi et al., 2012; Kim et al., 2016; Kim et al., 2016; Kim et al., 2019). DCE also has an advantage that it enables to derive individual preference for each attribute constituting a product or service (Kim et al., 2019; Shin et al., 2016).

DCE can solve multi-collinearity between attributes by using fractional factorial designs such as orthogonal design (Thyne et al., 2006; Danaher, 1997; Haider & Ewing, 1990). Individuals respond repeatedly to the process of choosing the most preferred alternative from the choice set that is composed of alternatives obtained through orthogonal design (McCullough, 2002). It is common to design a DCE with an adequate number of attributes as too many attributes consisting the alternatives may lead to lack in accuracy of preference analysis (Phelps & Shanteau, 1978). DCE is particularly useful in early-stage products and service preference analysis as it uses a hypothetical alternative (Kim et al., 2019; Huh et al., 2014; Koo et al., 2014). Researchers put their best effort to design each attribute independently, but insignificant preference estimates can be derived from DCE because the additive separability of the attributes is not considered in the preference analysis. This is especially true in the fields where actual products and services are being designed. Kim et al.(2017) argues that additive separability assumption is not satisfied when respondents of DCE lack an experience with the topic and thereby lack an understanding of attributes consisting an alternative. Additive separability can also become problematic when DCE include too many attributes and thereby increase cognitive burden to respondents (Moon, 2017).

Choice model largely consists of three rules. First rule is valuation rule which is about how each attributes being evaluated. Second rule is integration rule that sets relationship of valuation of attributes to perceived utility of alternative. Final rule is choice rule which explains overt behavior of respondents (Meyer & Johnson, 1995).

A number of recent DCE studies focuses on advancing valuation rule and choice rule by incorporating additional behavioral stage in traditional choice model (Kim, 2019; Lee, 2019; Lim, 2016; Moon, 2017; Park, 2019; Park, 2020). Although the author investigated the previous studies at each stage and presented them in the subsequent section, the methodological improvement is highly focused on Section 2.1.2 integration rule. This study is based on the benefit-based model with a nested satiation structure of Kim et al. (2017), and presents models that examine the rule of diminishing marginal utility in utility and benefit levels.

I will further mention in detail on Chapter 5 conclusion, but it is important to note that the benefit-based model is a rule mainly applied to integrating rule. Benefit-based model can flexibly encompass other behavioral choice models that correspond to valuation rule or choice rules such as reference-dependent preference model (Kim, 2019), uncertainty and information search model (Lim, 2016), time discounting model (Lee, 2019), Attribute non-attendance model (Moon, 2017), random regret minimization model (Park, 2019).

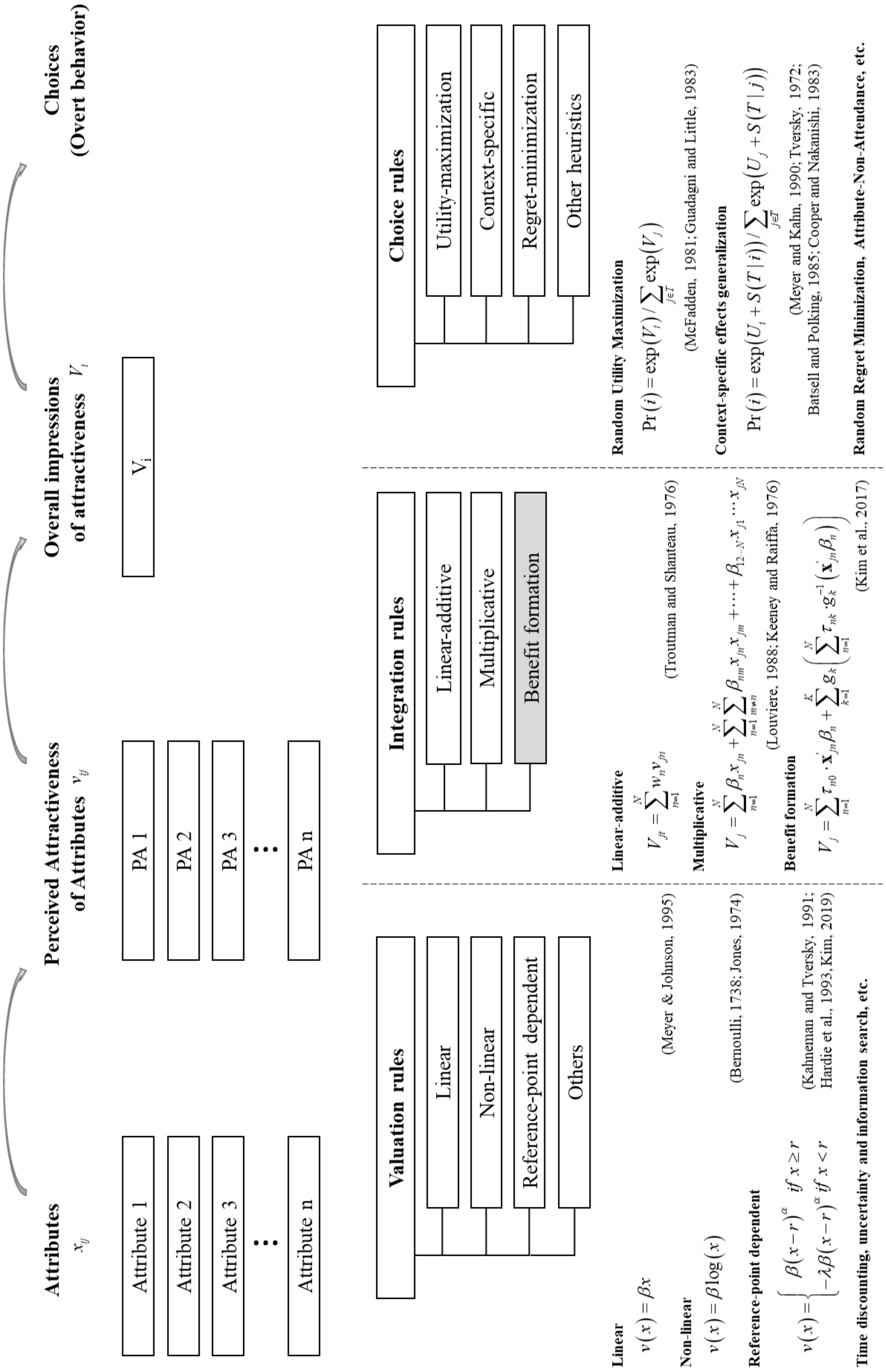


Figure 1. Discrete Choice Experiment framework

2.1.1 Valuation Rules

Linear Attribute Valuation Rule

Linear attribute valuation rule, which is the most basic method of valuation rule, which is a method of evaluating partial value of attribute x, is a method widely used in standard multinomial logit and mixed logit, which are general discrete selection experiment methodologies (Meyer & Johnson, 1995). It can be expressed as Equation (2.1) and the coefficient of β is expressed as a positive sign or a negative sign depending on the direction of preference.

$$v(x) = \beta x \quad \text{Eq. (2.1)}$$

Non-linear Attribute Valuation Rule

In simple linear discrete choice models, bias can be caused by errors from inefficient estimates (Yatchew and Griliches, 1984). There are a number of studies that has examined nonlinear property of utility using logarithmic functions, power functions, and power-exponential functions (De Palma et al., 2008; Holt & Laury, 2002). These nonlinear function has the advantage of being able to reflect various attitudes toward uncertainty of respondents (De palma et al., 2008). Bernoulli (1738) and Jones (1974) nonlinear preference valuation rule with log specification is widely used as a method that reflects nonlinear satiation preference.

$$v(x) = \beta \log(x) \quad \cdots\cdots \text{Eq. (2.2)}$$

In a similar form, the Dixit and Stiglitz (1977) model of power function (x^{α}) exists. Here α is set to be greater than 0 and less than or equal to 1 to implement a concave utility curvature.

$$v(x) = \beta x^{\alpha},\ 0 < \alpha \leq 1 \quad \cdots\cdots \text{Eq. (2.3)}$$

Prospect theory, which reflects diminishing marginal utility but also reflects the important concept such as the reference point and loss aversion (Tversky & Kahneman, 1992; 2013), has not been conducted in this study. Benefit based model can also be extended by reflecting the reference point, r and loss aversion parameter, λ can also be represented in the form Kim (2019) or Baillon, Bleichrodt & Spinu (2020) as in equation (2.4).

$$v(x) = \begin{cases} \beta(x-r)^{\alpha} & if\ x \geq r \\ -\lambda\beta(x-r)^{\alpha} & if\ x < r \end{cases} \quad \cdots\cdots \text{Eq. (2.4)}$$

2.1.2 Integration Rules

Linear Additive Model

The linear additive approach proposed by Green and Srinivasan (1978) is a basic concept of the integration rule and the most widely used approach (Kahn & Meyer, 1991). Traditionally, the utility of alternative has been derived from linear-additive from each attribute part-worth (Chorus, 2014). Expressed as an equation, the utility for alternative *j* is the sum of the part-worth, v_{jn} of the *N* attributes that consist alternative *j*, as shown in equation (2.5).

$$V_j = \sum_{n=1}^{N} v_{jn} \qquad \cdots\cdots \text{Eq. (2.5)}$$

There also exists an approach of assigning weights for each attribute as shown in Eq. (2.6) to reflect heterogeneous weights for each attribute (Lynch 1985; Russo & Dosher, 1983; Troutman & Shanteau, 1976; Wilkie & Pessemier, 1973), but it does not deviate from linear additive method.

$$V_{jt} = \sum_{n=1}^{N} w_n v_{jn} \qquad \cdots\cdots \text{Eq. (2.6)}$$

As shown in the above equations, when there are *N* attributes that consist alternative *j*, and composed of a linear combination, the utility equation is as follows (2.7).

$$\begin{aligned} u_j\left(x_{j1}, x_{j2}, \ldots, x_{jN}\right) &= \sum_{n=1}^{N} w_n\left(x_{jn}\right) + \varepsilon_j \\ &= \sum_{n=1}^{N} \mathbf{x}_{jn}\boldsymbol{\beta}_n + \varepsilon_j \end{aligned} \quad \cdots\cdots \text{Eq. (2.7)}$$

Here, $w_n\left(x_{jn}\right) = \mathbf{x}_{jn}\boldsymbol{\beta}_n$ corresponds to the linear combination of the attribute. Dellaert et al. (2018) expressed this linear relationship in the traditional DCE as shown in Figure 2. for attribute, utility, and choice relationships. .

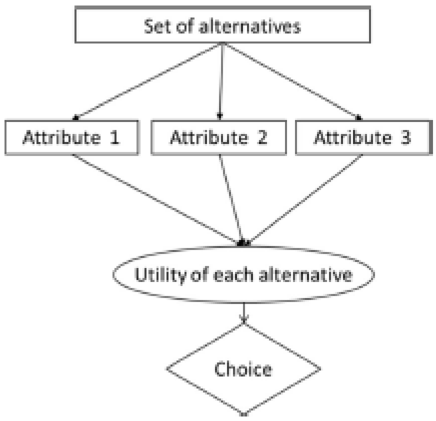


Figure 2. Structure of traditional discrete choice model

Multiplicative Model

Louviere (1988) argued that it is appropriate to use a multiplicative model that includes a cross term rather than linear-additive model that simply sum the part-worth of the attribute for attributes with substitution and complementary relationships. This approach also has strengths that it can capture individuals' decision-making strategies (Dellaert et al., 2018). This multiplicative approach has the advantage of being able to capture the substitution and complementary relationship between attributes, but as the number of attributes increases, the number of crossing terms increases exponentially, making it difficult to interpret what each term means. In the discrete choice model, such multiplicative integration model between attributes did not make much progress after the multiplicative method proposed by Keeney & Raiffa (1976) and Louviere (1988). Assuming that there are N attributes constituting alternative j, and they are constructed with utility under the multiplicative integration rule, the utility equation for the alternative is as Eq. (2.8).

$$V_j = \sum_{n=1}^{N} \beta_n x_{jn} + \sum_{n=1}^{N} \sum_{m \neq n}^{N} \beta_{nm} x_{jn} x_{jm} + \cdots + \beta_{12 \cdots N} x_{j1} \cdots x_{jN} \quad \cdots\cdots\cdots\cdots \text{Eq. (2.8)}$$

Discrete Choice with Simultaneous Equation Models

This section introduces studies that explain the relationship between preference and utility for attributes through a black-box structure. In this approach, the structure of the error term is captured by utilizing the latent structure.

DCE models introduced in this section correspond to the efforts of scholars who attempted behavioral interpretation using elaborate econometric methods. Initially, a model improvement was made that focuses on the error structure in the model for the substitution relationship between observed attributes, but in recent years, interest has been shifted to a psychological integration model as behavioral economics becomes more popular (Dellaert et al. 2018).

This section briefly reviews how it has been extended over the years to incorporate various behavioral effects into the traditional discrete choice model. As shown in Figure 3, these studies focus on the systematic component of the model that captures the change in the decision-making process or decision weight. Individuals evaluate the attractiveness of the attribute level and integrate this evaluation into the overall utility of each alternative.

Burke et al. (2020) utilized multiple mediator variable for explaining the heterogeneity of the effects of each attribute. Other studies that expanded this black-box structure models include Chandukala et al. (2011), Luo et al. (2008), Ashok et al. (2002).

The aforementioned studies have the advantage that more intuitive interpretation is possible by separating the direct effect, γ of the attribute on the utility and the indirect effect, $\alpha\beta$ on the utility through the latent variable, as shown in Figure 3 below. There is also an advantage that possible correlation between the error terms can be solved by using the latent variable. Nevertheless, there is also a constraint that this approach should have a rich behavioral economic basis for interpreting the indirect effects of unobserved latent variables (Dellaert, 2018).

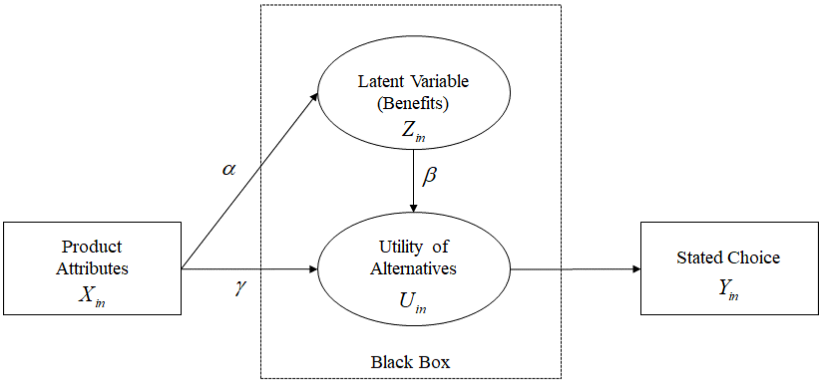


Figure 3. Black-box structure

Dellaert et al. (2018) used a conceptual model that classifies individual decision-making into multiple goals. The proposed model separated the observable attribute space and the unobservable goal space, and introduces the goal space to see whether the attributes contribute to achieving the goal. In studies using a similar approach, researchers are focusing on enriching evidences through observable choice data because researchers cannot directly confirm the basic assumptions used to construct the goal space. This dissertation is a study in which probabilistic grouping is performed using the assumption of satiation, which has already been proven by numerous studies.

Benefit-based Models

There are a number of studies presenting a benefit-based discrete choice model (Arentze et al., 2015; Ben-Akiva et al., 2002; Burke et al., 2020; Dellaert et al., 2008; Dellaert et al., 2018; Hur & Allenby, 2020; Kim et al., 2016; Swait et al., 2018). In this section, Dellaert et al. (2008) and Arentze et al. (2015) which assumes attributes are explicitly mapped to multiple benefits, and Kim et al. (2017) which assumes one attribute is probabilistically mapped with only one benefit is introduced and compared.

Dellaert et al. (2008) argued that the definition of benefit should be based on basic needs such as safety and convenience, or needs derived from these basic needs. This definition of benefit with a solid academic basis serves as the basis for the researcher's hypothesis and explicit mapping between attributes and benefits. Arentze et al. (2015) applied an integrated rule of matching individual attributes and benefits, assuming a situation in which the mapping relationship between specific attributes and benefits is explicit. Dellaert et al. (2018) generalized this benefit-based DCE relationship and expressed it as Figure 4.

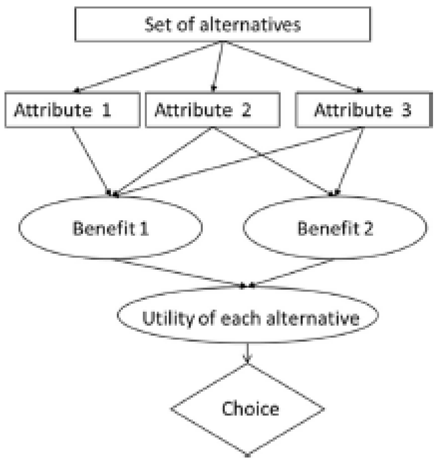


Figure 4. Structure of benefit-based discrete choice models

Unlike the studies mentioned above, Kim et al. (2017) assumed a probabilistic mapping of the benefits of each attribute. Individuals viewed each attribute as probabilistic mapping to one benefit, and a nested satiation structure of utility was applied that follows the law of diminishing marginal utility [2]. Specifically, to express satiation, the benefit-utility function was used as a logarithmic function to express the law of marginal diminishing utility while maintaining the monotonicity and subadditivity properties (McFadden & Train, 2000).

Kim et al. (2017) confirms which benefits are grouped based on posterior probabilities from respondents' choice data itself. This is major difference between the approaches in the other benefit-based DCE studies mentioned earlier. In addition, since there is no need for additional questionnaire items to utilize latent variables in the questionnaire, it has an advantage of being easily applied to traditional discrete choice experiments. The detailed model will be examined in detail in Section 3.1.

2.1.3 Choice Rules

Standard Logit Model

Random utility theory has established itself as the dominant behavioral decision theory in economics. Traditional consumer behavior studies mainly use a discrete choice model based on a random utility maximization to understand the preferences of decision makers (Chorus, 2012). Specifically, decision makers choose the alternative that gives the

[2] DCE models using the existing linear additive integration rule cannot avoid the problem of overlapping features between multiple properties. For an example, please refer to the toothpaste example presented by Kim et al. (2017, p.54).

highest utility in random utility theory.

The standard logit model, which provides the basis for the discrete selection model, has the advantage that the likelihood can be estimated using maximum likelihood estimation method as the choice probability in equation takes a closed form (Train, 2009). Utility of respondent *h* achieved from choosing alternative *j* is as following Eq. (2.9) (McFadden, 1973; Train, 2009).

$$U_{hj} = V_{hj} + \varepsilon_{hj} = \boldsymbol{\beta}_k^{'} \mathbf{x}_{jn} + \varepsilon_{hj} \quad \cdots\cdots \text{Eq. (2.9)}$$

Here, the utility of individual respondent is explained by a deterministic term (V_{hj}), which is a part that can be explained like an attribute of an alternative, and a stochastic term (ε_{hj}), which is an unexplainable part with uncertainty. The deterministic term is generally expressed as the product of the level vector, x_n of the attribute *n* constituting the alternative *j* and the parameter corresponding to the attribute *n*. The discrete choice model can also be classified by the assumptions used in the stochastic term. In general, the stochastic term ε_{hj} is assumed to have independently, identically distributed type 1 extreme value distribution. In this case, the density of the stochastic term is defined as the following Eq. (2.10) (Train, 2009).

$$f(\varepsilon_{hj}) = e^{-\varepsilon_{hj}} e^{e^{-\varepsilon_{hj}}} \quad \cdots\cdots \text{Eq. (2.10)}$$

According to the random utility maximization choice rule, the probability P_{nj} of the respondent *h* choosing an alternative *j* that provides the greatest utility within the choice set is derived as the following Eq. (2.11) (Train, 2009).

$$\begin{aligned} P_{hj} &= P(U_{hj} > U_{hi},\ \forall j \neq i) \\ &= P(V_{hj} + \varepsilon_{hj} > V_{hi} + \varepsilon_{hi},\ \forall j \neq i) \\ &= P(\varepsilon_{hi} < \varepsilon_{hj} + V_{hj} - V_{hi},\ \forall j \neq i) \end{aligned} \quad \cdots\cdots \text{Eq. (2.11)}$$

Choice probability Eq, (2.11) can be derived as the following equation (2.12) using the density equation of the stochastic term, and is expressed in a closed form (McFadden, 1981; Guadagni & Little, 1983).

$$P_{hj} = \int \left(\prod_{j \neq i} e^{e^{-(\varepsilon_{hj} + V_{hj} - V_{hi})}} \right) e^{-\varepsilon_{hj}} e^{e^{-\varepsilon_{hj}}} d\varepsilon_{hj} = \frac{e^{V_{hj}}}{\sum_i e^{V_{hi}}} = \frac{e^{\beta_n' x_{jn}}}{\sum_i e^{\beta_n' x_{in}}} \quad \cdots\cdots \text{Eq. (2.12)}$$

If there are multiple choice sets *T* to be answered by individual *h*, the likelihood of individual *h* choosing alternative *j* is expressed as Eq. (2.13) (Train, 2009). Here y_{hjt} is defined to have value “1” if individual *h* chooses alternative *j* from choice set *t* and “0” otherwise.

$$P_h = \prod_t \prod_j (P_{hjt})^{y_{hjt}} \quad \cdots\cdots\cdots \text{Eq. (2.13)}$$

Assuming that the individual choice is independent from the other individuals choices, the likelihood of the sample is expressed as the following Eq. (2.14) (Train, 2009).

$$Likelihood = \prod_{h=1}^{H} P_h = \prod_{h=1}^{H} \prod_t \prod_j (P_{hjt})^{y_{hjt}} \quad \cdots\cdots\cdots \text{Eq. (2.14)}$$

Heuristic Models

Studies utilizing the discrete choice model based on the random utility maximization(RUM) choice rule analyze choices and preferences under the assumption that individuals take a complete reward decision rule for all attributes that constitute the choice set (McFadden & Train, 2000; Leong & Hensher, 2012).

The discrete choice model based on the RUM choice rule is known to be a useful and effective method for analyzing the preferences of decision makers, but the heuristic choice rule based on behavioral economic insights has expanded in various directions since 2000. Representative heuristic choice rules are introduced.

The use of cutoff rules to screen if the attributes do not achieve a certain level (Swait, 2001), use of conjunctive or disjunctive rules (Gillbride & Allenby, 2004; Hauser et al., 2010), attribute non-attendance that does not consider specific attribute (Moon, 2017; Park, 2019), change of choice rule according to the complexity of the presented choice set (Swait & Adamovicz, 2001), random regret minimization (Chorus et al., 2008), etc. The mentioned models reinforce the existing discrete choice model by adding heuristic step in choice model. Dellaert et al. (2018) expressed this attribute-heuristic-selection relationship as in Figure 5 in behavioral DCE.

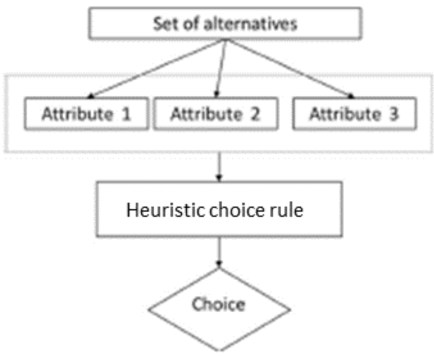


Figure 5. Structure of discrete choice model with heuristic choice rule

There are also models that assume different choice can be made depending on the context of the choice (Meyer & Kahn, 1990; Tversky, 1972; Batsell & Polking, 1985; Cooper & Nakanishi, 1983).

2.2 Satiation

Term satiation used in habit formation utility model literature refers to condition when previous consumption decreases current marginal utility[3] (Iannaconne, 1986). In choice model literature, term satiation also refers to condition when diminishing marginal utility is observed within the utility of alternatives presented in DCE (Bhat, 2008; Kim et al. 2017).

Satiation in attribute level

In the standard DCE model, for the utility of the alternative, the linear attribute valuation rule was used to determine the partial utility of the attributes constituting the alternative, and the linear additive integration rule as Eq. (2.1) was used as a rule for integrating attributes. Use a random utility maximization choice rule.

When analyzing satiation using the standard discrete selection model, there is a method of using a non-linear valuation rule for a single continuous attribute such as Eq. (2.2) and Eq. (2.3), but this approach only enables to analyze satiation in attribute level and does not solve additivity separability problem in DCE between attributes.

Satiation in benefit level

Kim et al. (2017) proposes benefit having satiation property, which is satisfied when

[3] Opposite term is addiction

monotonicity and subadditivity applies. Further details in model specifications will be explained in Section 3.1. In this section, I introduce nested satiation structure proposed by Kim et al. (2017) with a glimpse. The utility of option j is expressed as the sum of the part-worths of the benefits and is represented as Eq. (2.15). Given attribute levels of N attributes in option j, consumers partition attributes N, into benefits K, with $K < N$. $g(\cdot)$ is a concave function such a log or power function with power less than or equal to 1 as in Eq. (2.2) or Eq. (2.3).

$$u_j = \sum_{n=1}^{N} \tau_{n0} \cdot \mathbf{x}'_{jn}\beta_n + \sum_{k=1}^{K} g_k \left(\sum_{n=1}^{N} \tau_{nk} \cdot g_k^{-1}\left(\mathbf{x}'_{jn}\beta_n\right) \right) + \varepsilon_j \quad \cdots\cdots \text{Eq. (2.15)}$$

Satiation in utility level

Satiation can be observed in attribute level but also be observed in benefit level and utility level. A special case when K=1 and all assignment probability of attribute is assigned to benefit 1 ($\tau_{n1} = 1$ for all n) when satiation is in whole utility level. It can be represented as Eq. (2.16). This model will also be discussed in Section 3.2.

$$u_j = g\left(\sum_{n=1}^{N} g_k^{-1}\left(\mathbf{x}'_{jn}\beta_n\right) \right) + \varepsilon_j \quad \cdots\cdots \text{Eq. (2.16)}$$

2.3 Factor Approach

Factor Analysis

The factor analysis technique was created by attempts to explain behavior by constructs and attempts to explain people by individual differences in psychology by Spearman (1904). Principal Component Analysis(PCA) which is a technique to reduce dimensions developed by Pearson (1901) also approaches in similar manner.

Thompson(1920) later advanced factor analysis by using sampling theory of mental abilities. He used assumption that intelligence consists of a narrowly defined set of abilities and each test uses samples of these abilities. The correlation between the two tests occurs because the two competency samples overlap.

Thurstone (1938) used intelligence tests that yield a seven primary mental ability profile of the individual performance and introduced concept of multiple factor model or common factor model. Practical question is about how to decide the adequate number of factors in factor model. Guttmann(1954) used the number of eigenvalues greater than 1 in the correlation matrix as a number of factors, Cattell(1966) used scree test but number of scholars criticized that number of factors can be varied according to conditions (Zwich & Velicer, 1986; Hakstian et al., 1982).

Factor Augmented Vector Auto-Regression Model(FAVAR)

FAVAR is model suggested by Bernanke et al.(2005) that enrich variable subsets that constitute structural vector autoregression(VAR) model. Standard VARs employ less than eight variables but FAVAR allows to use more than 150 variables by reducing dimensions using factors. In standard VAR, additional inclusion of variables severely limits analysis due to degree-of-freedom problems (Bernanke et al., 2005).

Standard VAR method by Christiano et al. (1999) is quite commonly used, and Bernanke et al. (2005) also applied the identification method of Christiano et al. (1999) to the FAVAR model. In the existing literature, there are many cases in which base model is determined and then added variable to the basic model one by one to analyze the effect of each variable (e.g. Christiano et al., 1994; 1997; 1999).

FAVAR is an approach that combines standard VAR with factor analysis simultaneously by using Bayesian likelihood method and Gibbs sampling. This property lessens the burden of standard VAR requiring precise theoretical constructs (Bernanke et al., 2005). This strength is worthy of attention to the readers as benefit-based model in DCE also does not require precise theoretical constructs required in other DCE models that use latent construct. To conclude, using factor augmented approach to other conventional method enables information extraction without further theoretical constructs.

Latent Class Model

Similar approach is the latent class model which assumes that the estimated variable can be estimated as a discrete mixed distribution. McFadden (1986) recognized the possibility of using latent variables in analyzing choice behavior.

Often referred to as finite-mixture model is used to understand systematic heterogeneity within latent group and it is said that respondent segments with different utility structures can be divided into several mass points (Boxall & Adamowicz, 2002; Valeri, 2016). Swait (1994) used latent class model to conduct market segmentation and analyze choice behavior simultaneously using eight psychometric dimensions. In latent class model, the optimal number of segments are often selected using Akaike Information Criteria or Bayesian Information Criteria (Boxall & Adamowicz, 2002).

Benefit-based model

There can be other method to decide number of benefit groups in benefit-based model. This is practically important question as benefit groups capture the information necessary to properly model the consumer preference. I collectively referred to literatures of Bai & Ng (2002), Bernanke et al. (2006) in FAVAR model, Boxall & Adamowicz (2002) in latent class model. However, fore-mentioned literatures does not address the question of how many benefit groups should be included in benefit-based model. This research applied Kim et al.(2017) as a basis method to decide number of benefit groups, and decided the number of benefit groups that allows more parsimonious interpretation.

2.4 Research Motivation

In the standard DCE model, the utility of the alternative is derived by first, using the linear attribute valuation rule to determine the partial utility of the attributes constituting the alternative. Second, linear additive integration rule is used as a rule for integrating partial utility of the attributes to utility. Finally, random utility maximization(RUM) is used as a choice rule.

When analyzing satiation using the standard DCE model, there is a method of using a non-linear valuation rule for a single continuous attribute, but the additive separability problem between these attributes cannot be resolved. Also, satiation can only be observed at the attribute level and not in overall utility or benefit level.

Additive separability mentioned by Kim et al. (2017) becomes problematic when individuals may not be able to think of some attributes separately from others. This reason can be due to various reasons such as lack of experience and lack of understanding of attributes. It is appropriate to consider that the partial utilities of properties within the same benefit are satiate, and the additive separability assumption used in traditional DCE needs to be relaxed. Johnson and Meyer (1984) also agree that using additive separability assumption may not sufficiently explain individual choices, making it difficult to derive accurate implications.

The challenge in the benefit model is to identify the benefit formation structure that is not exposed in reality. In a benefit-based DCE model other than Kim et al. (2017) such as

Arentze et al. (2015) and Dellaert et al. (2018), it was assumed that the relationship between attributes and benefits was known in advance and used precise theoretical latent construct that constitute benefit structure. This dissertation follows the Kim et al. (2017) model, which identifies the benefit structure without any prior knowledge or additional assumptions related to benefit formation. This benefit-based approach has practical strength that it does not require a precise theoretical construct or an additional questionnaire to make use of latent variable(s). Research motivation is to extract decision importance information from choice data and increase predictive fit of the benefit-base model by introducing benefit scale parameter using Bayesian learning approach.

In Kim et al. (2017) model, scale heterogeneity between benefits is not considered. In this dissertation, proposed models are compared with standard multinomial logit (MNL) model and benefit-based model by Kim et al. (2017). First proposed model is benefit-scale model is a model that specifies the scale parameter to each benefit in benefit-based model by Kim et al. (2017). Second proposed model is satiation in utility model, which assumes the dimension of satiation takes place in the overall utility level rather than the benefit level. Third proposed model assumes benefit grouping of attributes from the estimated assignment probability from the benefit-scale model. Last proposed model, demographic indexed benefit-scale model, incorporates demographic variables in scale parameter.

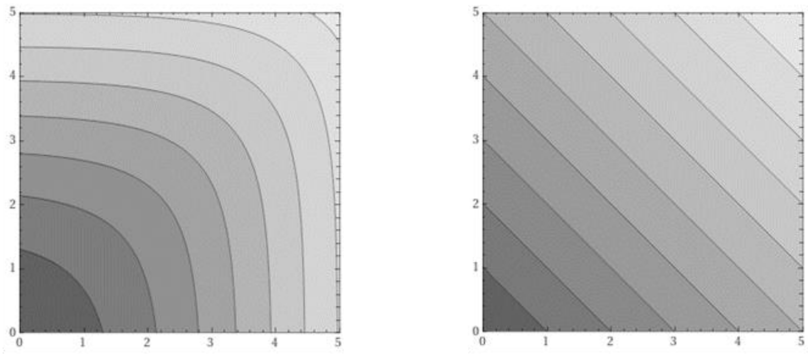
Chapter 3. Model

3.1 Benefit-based Model

3.1.1 Overview of the Model

Kim et al. (2017) grouped attributes into one or several benefit(s) through one on one probabilistic mapping through a nested satiation structure of alternative utility. This nested structure allows diminishing marginal utility within a benefit. Benefit-based model groups product or service attributes into benefits and utilizes the assumption that these grouped attributes exhibit property of diminishing marginal utility within benefit.

It is important to note that there exist unique attributes that do not exhibit diminishing marginal utility property within benefit. Since these attributes provide independent utility regardless of the presence or absence of other attributes, it provides important management implication in the perspective of product/service designers.



Contour plot of $g\left(g^{-1}(a_1)+g^{-1}(a_2)\right)$ **Contour plot of** a_1+a_2

Figure 6. Satiation within benefit

3.1.2 Model Specification

Assume that there are a total N attributes and K mutually exclusive benefit groups that can be distinguished ($K<N$). If alternative j is selected, N attributes are grouped into K benefits, and if there are M_k attributes included in benefit group k, the utility is as Eq. (3.1). Specifically, the form of Eq. (3.1) is expressed as a linear combination of benefit function.

$$u_j = \sum_{k=1}^{K} b_k\left(a_{jk1}, a_{jk2}, ..., a_{jkM_k}\right) + \varepsilon_j \quad \cdots\cdots \text{Eq. (3.1)}$$

Here, a_{jkm} denotes the m-th attribute level within k benefits in alternative j. In this case, the benefit function b_k is defined as follows to assume that there is satiation in utility within the attributes grouped in the benefit.

$$\begin{aligned} b_k\left(a_{jk1}, ..., a_{jkM_k}\right) &= g_k\left(\sum_{m=1}^{M_k} g_k^{-1}\left(a_{jkm}\right)\right) \\ g_k\left(a_{jkm}\right) &= sign\left(a_{jkm}\right)\log\left(\left|a_{jkm}\right|+1\right) \end{aligned} \quad \cdots\cdots \text{Eq. (3.2)}$$

As can be seen in Eq.(3.2), $g_k(\bullet)$ takes the form of a log function that can satisfy both conditions of monotonicity and subadditivity so as to satisfy the satiation of the utility. It is also generalized using $sign(a_{jkm})$ which returns 1(or -1) when a_{jkm} is positive (or negative) to analyze disutility from an attribute. $g_k(\bullet)$ is continuous and second order differentiable, monotonically increasing, and $g_k(a_{jkm}) = 0$ when $a_{jkm} = 0$. Also not that, $a_{jkm} = 0 \rightarrow g_k(a_{jkm}) = 0$ enables the function to be concave when positive, and convex when negative. Expressing Eq. (3.1) and Eq. (3.2) with a linear combination $a_{jkm} = \mathbf{x}_{jkm}\boldsymbol{\beta}_{kn}$, Eq. (3.3) can be derived.

$$b_k\left(a_{jk1},\ldots,a_{jkM_k}\right) = g_k\left(\sum_{m=1}^{M_k} g_k^{-1}\left(a_{jkm}\right)\right) = g_k\left(\sum_{m=1}^{M_k} g_k^{-1}\left(\mathbf{x}_{jkm}\boldsymbol{\beta}_{kn}\right)\right) \quad \cdots\cdots\text{Eq. (3.3)}$$

Random variable τ_{nk} is used to group *N* attributes into *K* benefits. τ_{nk} has a value of 1 when the *n*-th attribute is assigned to *k* benefit, and 0 when not.

$$\begin{aligned}
&u_j = \sum_{k=1}^{K} g_k\left(\sum_{n=1}^{N} \tau_{nk} g_k^{-1}\left(\mathbf{x}_{jn}^{'}\boldsymbol{\beta}_n\right)\right) + \varepsilon_j \\
&\tau_n^* \in \{1, 2, \ldots, K\} \qquad \cdots\cdots\text{Eq. (3.4)} \\
&\tau_{nk} \sim Multinomial\left(\theta_{n1},\ldots,\theta_{nK}\right) \\
&\theta_{n1},\ldots,\theta_{nK} \sim Dirichlet\left(\eta_{n1},\ldots,\eta_{nK}\right)
\end{aligned}$$

Attributes that are not grouped into benefits are separated into a null group and are not included in the nested satiation structure of utility as Eq. (3.5).

$$u_j = \sum_{n=1}^{N} \tau_{n0} \cdot \mathbf{x}'_{jn}\beta_n + \sum_{k=1}^{K} g_k \left(\sum_{n=1}^{N} \tau_{nk} \cdot g_k^{-1}\left(\mathbf{x}'_{jn}\beta_n\right)\right) + \varepsilon_j \quad \cdots\cdots \text{Eq. (3.5)}$$

Models that can encompass various behavioral effects in the traditional choice model have been developed, but many studies have focused on heterogeneity of preference (McFadden & Train, 2000) and heteroscedasticity between choices or individuals (Fiebig et al., 2010). In the benefit-based model, the assumption that individual *h* groups benefits differently is modeled as Eq. (3.6), and the assumption that estimated parameter for individual *h* is heterogeneous is modeled with Eq. (3.7).

$$\tau_{hn}^{*} \sim Multinomial_{K+1}\left(\theta_{n0},...,\theta_{nK}\right) \quad \cdots\cdots \text{Eq. (3.6)}$$

$$\beta_h \sim [\beta'_{h1},...,\beta'_{hN}]' \sim N\left(\bar{\beta}, V_\beta\right) \quad \cdots\cdots \text{Eq. (3.7)}$$

Finally, the specification of the model repeated *t* times is as Eq. (3.8).

$$u_{hjt} = \sum_{n=1}^{N} \tau_{hn0} \cdot \left(\mathbf{x}'_{hjnt}\boldsymbol{\beta}_{hn}\right) + \sum_{k=1}^{K} g_k \left(\sum_{n=1}^{N} \tau_{hnk} \cdot g_k^{-1}\left(\mathbf{x}'_{hjnt}\boldsymbol{\beta}_{hn}\right)\right) + \varepsilon_{hjt} \quad \cdots\cdots \text{Eq. (3.8)}$$

3.1.3 Schematic illustration of the Model

To illustrate the model, I will use example when N =13, K =2 as following figure 7. Given option j in a choice task, consumers partition N attributes into K mutually exclusive benefits B_k ($K < N$).

In the process of integration rule, we define τ_n^* as auxiliary variable that describes the attribute to benefit(A-B) mapping. To illustrate in previous N =13, K =2 setting, $\tau_n^* = \{1, 2\}$ *for* $n = 1, 2, \cdots, 13$. But A-B mapping are unknown that we need to estimate.

$$u_j = \sum_{k=k_1,k_2} g_k \left(\sum_{n=1}^{13} \tau_{nk} \cdot g_k^{-1} \left(x_{jn}^{'} \beta_n \right) \right) + \varepsilon_j \quad \cdots\cdots\cdots\text{Eq. (3.9)}$$

To account for heterogeneity within respondents probabilistic modeling of the individual assignment τ_n^* is required. $\tau_{hn}^* \sim Multinomial_K\left(\theta_{n1}, \theta_{n2}, \cdots, \theta_{nK}\right)$, where θ_{nk} indicates the probability of assigning attribute *n* to benefit *k*.

Also, part-worth parameters should be considered as heterogeneous, $\boldsymbol{\beta}_h = \left[\boldsymbol{\beta}_{h1}^{'}\ \boldsymbol{\beta}_{h2}^{'}\ \cdots\ \boldsymbol{\beta}_{hN}^{'}\right]' \sim N\left(\bar{\boldsymbol{\beta}}, V_\beta\right)$ and choice specific subscript t is also considered as follows

$$u_{hjt} = \sum_{k=k_1,k_2} g_k \left(\sum_{n=1}^{13} \tau_{hnk} \cdot g_k^{-1} \left(\mathbf{x}'_{hjnt} \boldsymbol{\beta}_{hn} \right) \right) + \varepsilon_{hjt} \quad \cdots\cdots \text{Eq. (3.10)}$$

We employ standard multinomial logit model as benchmark for estimation of $\bar{\boldsymbol{\beta}}, V_\beta$

$$u_{hjt} = \sum_{n=1}^{N} \mathbf{x}'_{hjnt} \boldsymbol{\beta}_{hn} + \varepsilon_{hjt} \quad \cdots\cdots \text{Eq. (3.11)}$$

Let z_{hjt} be response of individual *h* to choice *t*, which is "1" when option *j* is chosen and "0" otherwise, then likelihood of the responses of individual given $\boldsymbol{\beta}_h, \left\{ \tau^*_{hn} \right\}$ is

$$l_h \left(\boldsymbol{\beta}_h, \left\{ \tau^*_{hn} \right\} \mid \left\{ z_{hjt} \right\} \right) = \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{\exp\left(\bar{u}_{hjt} \left(\boldsymbol{\beta}_h, \left\{ \tau^*_{hn} \right\} \right) \right)}{\sum_{j'=1}^{J} \exp\left(\bar{u}_{hj't} \left(\boldsymbol{\beta}_h, \left\{ \tau^*_{hn} \right\} \right) \right)} \right]^{z_{hjt}} \quad \cdots\cdots \text{Eq. (3.12)}$$

Where $\bar{u}_{hjt} \left(\boldsymbol{\beta}_h, \left\{ \tau^*_{hn} \right\} \right) = u_{hjt} - \varepsilon_{hjt}$.

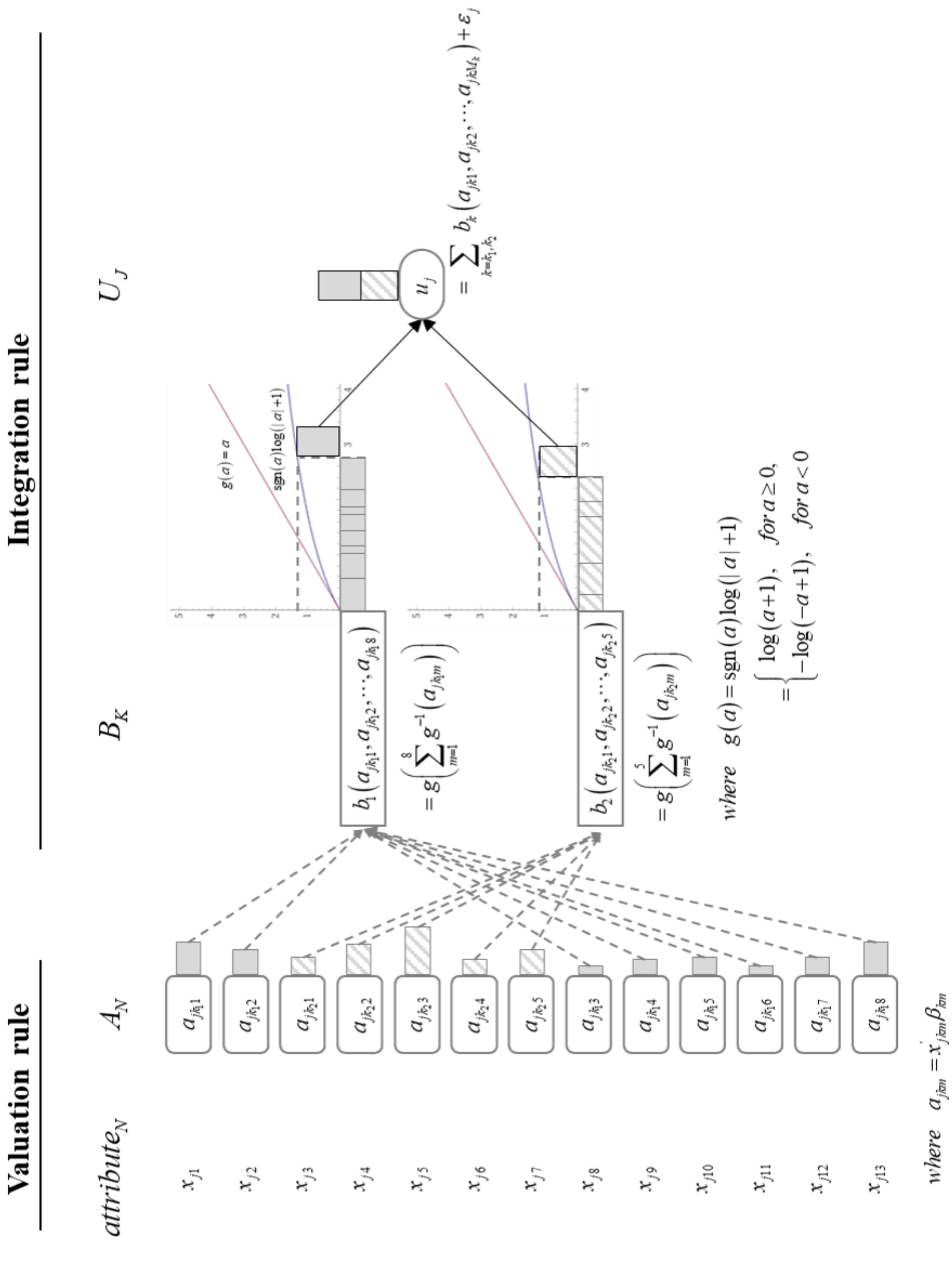


Figure 7. Schematic illustration of benefit-formation integration rule when K=2

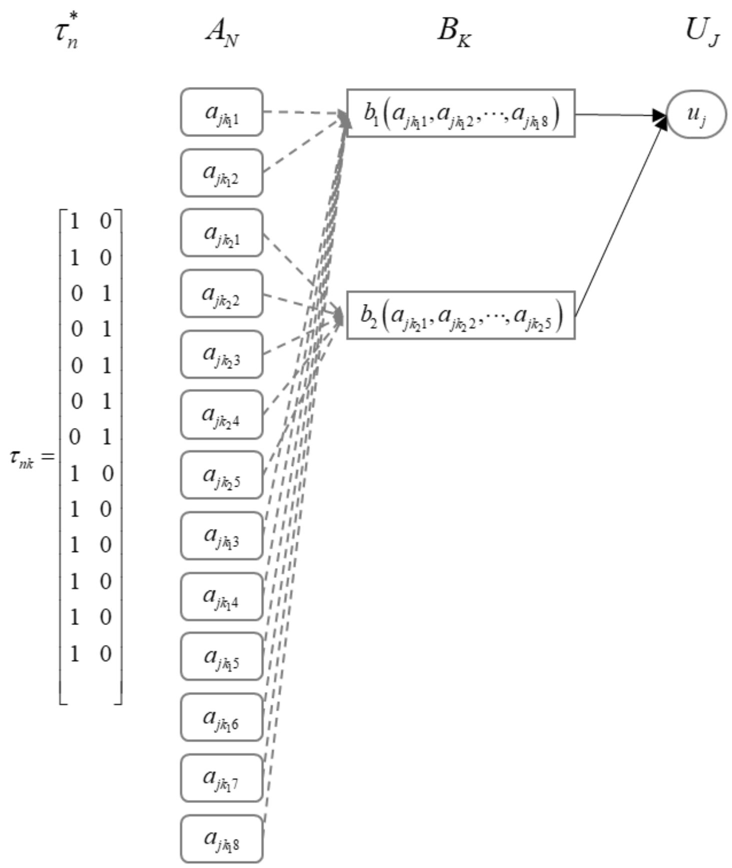


Figure 8. Illustration of attribute to benefit mapping with individual assignment

3.1.4 Estimation procedure

In Eq. (3.13), individual heterogeneity was reflected in the benefit-based model, and the MCMC method using the Metropolis Hastings algorithm was used. Detail estimation procedures are as follows.

$$u_{hjt} = \sum_{n=1}^{N} \tau_{hn0} \cdot \left(\mathbf{x}_{hjnt}^{'} \boldsymbol{\beta}_{hn} \right) + \sum_{k=1}^{K} g_k \left(\sum_{n=1}^{N} \tau_{hnk} \cdot g_k^{-1} \left(\mathbf{x}_{hjnt}^{'} \boldsymbol{\beta}_{hn} \right) \right) + \varepsilon_{hjt} \quad \cdots\cdots\cdots\cdots \text{Eq. (3.13)}$$

Step 1: Set initial values for $\boldsymbol{\beta}_h, \left\{ \tau_{hn}^{*} \right\}, \bar{\boldsymbol{\beta}}, \mathbf{V}_{\beta}, \left\{ \theta_{nk} \right\}$

Step 2: Generate $\boldsymbol{\beta}_h$ for h=1,2,…,H given $\left\{ \tau_{hn}^{*} \right\}, \bar{\boldsymbol{\beta}}, \mathbf{V}_{\beta}$ using random-walk Metropolis Hastings algorithms

$$\text{Draw } \boldsymbol{\beta}_h^{new} \text{ from } N\left(\boldsymbol{\beta}_h^{old}, d^2 \cdot \mathbf{V}_{\beta} \right), \quad set\, d = 0.3$$

$$\text{Accept } \boldsymbol{\beta}_h^{new} \text{ with } \Pr\left(accept \right) = \min \left[1, \frac{l_h \left(\boldsymbol{\beta}_h^{new}, \left\{ \tau_{hn}^{*} \right\} \mid \left\{ z_{hjt} \right\} \right) \cdot \phi \left(\boldsymbol{\beta}_h^{new} \mid \bar{\boldsymbol{\beta}}, \mathbf{V}_{\beta} \right)}{l_h \left(\boldsymbol{\beta}_h^{old}, \left\{ \tau_{hn}^{*} \right\} \mid \left\{ z_{hjt} \right\} \right) \cdot \phi \left(\boldsymbol{\beta}_h^{old} \mid \bar{\boldsymbol{\beta}}, \mathbf{V}_{\beta} \right)} \right]$$

Step 3: Generate τ_{hn}^{*} for n=1,2,…,N and h=1,2,…,H given $\tau_{h,-n}^{*}, \boldsymbol{\beta}_h, \left\{ \theta_{nk} \right\}$ following posterior multinomial distribution (excluded for K=0)

$$\tau_{hn}^{*} \mid \tau_{h,-n}^{*}, \boldsymbol{\beta}_h, \left\{ \theta_{nk} \right\} \sim Multinomial_K \left(\tilde{\theta}_{n1}, \tilde{\theta}_{n2}, \cdots, \tilde{\theta}_{nK} \right)$$

$$\text{where } \tilde{\theta}_{nk} = \frac{l_h \left(\tau_{hn}^{*} = k, \boldsymbol{\beta}_h, \tau_{h,-n}^{*} \right) \cdot \theta_{nk}}{\sum_{k'=1}^{K} l_h \left(\tau_{hn}^{*} = k', \boldsymbol{\beta}_h, \tau_{h,-n}^{*} \right) \cdot \theta_{nk'}}$$

Step 4: Generate $\bar{\boldsymbol{\beta}}, \mathbf{V}_{\beta}$ given $\{\boldsymbol{\beta}_h\}$ using Bayesian multivariate regression

$$\boldsymbol{\beta}_h = \bar{\boldsymbol{\beta}} + \varsigma_h, \quad \varsigma_h \sim N\left(0, \mathbf{V}_{\beta}\right)$$

$$\text{where } \mathbf{V}_{\beta} \sim \mathrm{IW}\left(\mathrm{nvar}+3, \left(\mathrm{nvar}+3\right) \cdot \mathbf{I}_{\mathrm{nvar}}\right), \quad \mathbf{I}_{\mathrm{nvar}} = \text{identity matrix}$$

Step 5: Generate $\{\theta_{nk}\}$ given τ^{*}_{hn} following posterior Dirichlet distribution (excluded for K=0)

$$\theta_{n0}, \theta_{n1}, \cdots, \theta_{nK} \sim Dirichlet\left(\eta_{n0} + \sum\nolimits_{h=1}^{H} \tau_{hn0}, \eta_{n1} + \sum\nolimits_{h=1}^{H} \tau_{hn1}, \cdots, \eta_{nK} + \sum\nolimits_{h=1}^{H} \tau_{hnK}\right)$$

where the prior $\eta_{nk} = 3$ for all n,k

Step 6: repeat step 2 through 5 using MCMC

3.2 Satiation in utility level model

3.2.1 Model specification

Satiation can be observed in whole utility level as in Eq. (2.16). A special case of benefit-based model when K=1 and τ_{n1} =1 for all n. Accounting heterogeneity for individual h, and repeated for choice task t, the final specification is as Eq. (3.14).

$$u_{hjt} = g\left(\sum_{n=1}^{N} g_k^{-1}\left(\mathbf{x}'_{hjnt} \boldsymbol{\beta}_{hn}\right)\right) + \varepsilon_{hjt} \qquad \text{Eq. (3.14)}$$

3.2.2 Estimation procedure

Step 1: Set initial values for $\boldsymbol{\beta}_h, \bar{\boldsymbol{\beta}}, \mathbf{V}_\beta$

Step 2: Generate $\boldsymbol{\beta}_h$ for h=1,2,…,H given $\bar{\boldsymbol{\beta}}, \mathbf{V}_\beta$ using random-walk Metropolis Hastings algorithms

$$\text{Draw } \boldsymbol{\beta}_h^{new} \text{ from } N\left(\boldsymbol{\beta}_h^{old}, d^2 \cdot \mathbf{V}_\beta\right), \quad set\, d = 0.3$$

$$\text{Accept } \boldsymbol{\beta}_h^{new} \text{ with } \Pr\left(accept\right) = \min\left[1, \frac{l_h\left(\boldsymbol{\beta}_h^{new} \mid \left\{z_{hjt}\right\}\right) \cdot \phi\left(\boldsymbol{\beta}_h^{new} \mid \bar{\boldsymbol{\beta}}, \mathbf{V}_\beta\right)}{l_h\left(\boldsymbol{\beta}_h^{old} \mid \left\{z_{hjt}\right\}\right) \cdot \phi\left(\boldsymbol{\beta}_h^{old} \mid \bar{\boldsymbol{\beta}}, \mathbf{V}_\beta\right)}\right]$$

Step 3: Generate $\bar{\boldsymbol{\beta}}, \mathbf{V}_\beta$ using Bayesian multivariate regression

$$\boldsymbol{\beta}_h = \bar{\boldsymbol{\beta}} + \varsigma_h, \quad \varsigma_h \sim N\left(0, \mathbf{V}_\beta\right)$$

$$\text{where } \mathbf{V}_\beta \sim \mathrm{IW}\left(\mathrm{nvar}+3, \left(\mathrm{nvar}+3\right) \cdot \mathbf{I}_{\mathrm{nvar}}\right), \quad \mathbf{I}_{\mathrm{nvar}} = \text{identity matrix}$$

Step 4: repeat step 2 through 3 using MCMC

3.3 Benefit-scale Model

3.3.1 Overview of the Model

Integration rule defines relationship between attribute valuation and utility. While Kim et al.(2017) model sets relationship between attribute to benefit with θ_{nk}, benefit to utility relationship is simply assumed one on one. In this section, I introduce scale parameter s_k for benefit to utility relationship.

Scale Parameter

If we look at the utility function in Eq.(3.2) for increasing a, it is expressed as Figure 9, and we can clearly see the satiation form. The marginal utility depends on the value of s_k at $a > 0$. In particular, the higher the value of s_k, the smaller the satiation.

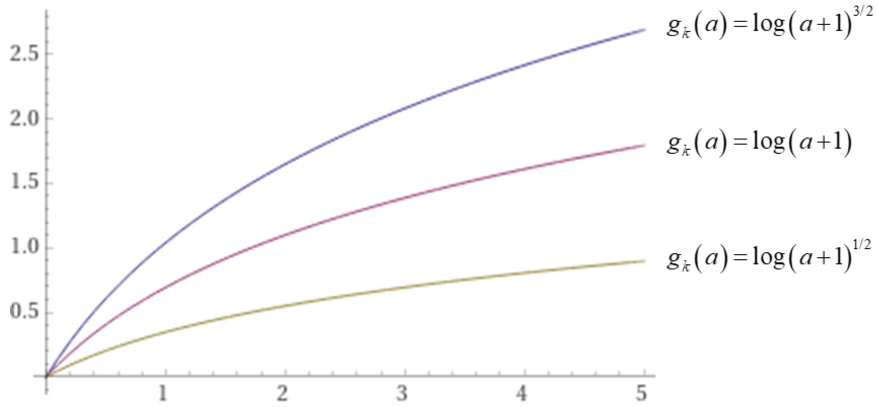


Figure 9. Difference in satiation curve

Bayesian Learning with softmax

In this model, scale parameter s_k is not estimated using Bayesian multivariate regression. Scale parameter s_k is extracted from Dirichlet distribution which uses κ_{htk} as a prior.

$$\kappa_{htk} = \begin{cases} 1, & if\ \ k = \arg\max_{k'}\left(\operatorname{soft}\max_{j'}\left(g_{htj'k'}\right)\right) \\ 0, & otherwise \end{cases} \quad \text{when } j' \text{ is chosen} \quad \cdots\cdots \text{Eq. (3.15)}$$

$$\text{Where } \operatorname{soft}\max_{j'}\left(g_{htj'k'}\right) = \exp\left(g_{htj'k'}\right) \Big/ \sum_j \exp\left(g_{htjk'}\right)$$

Bayesian learning method with softmax is used for κ_{htk}. Softmax is widely used in machine learning for categorization (Bishop & Christopher, 2006; Gao et al., 2017). In functional form, it corresponds to the logit probability used in the discrete choice model and represents decision importance in each choice task. Specifically, in Eq. (3.15), if the decision importance of a specific benefit *k'* in an individual *h* choice task *t* is highest, a value of 1 is assigned, and if not, a value of 0 is assigned.

$$\frac{s_1}{K}, \frac{s_2}{K}, \cdots, \frac{s_K}{K} \sim Dirichlet\left(\eta_1 + \sum_{h=1}^{H}\sum_{t=1}^{T}\kappa_{ht1}, \eta_2 + \sum_{h=1}^{H}\sum_{t=1}^{T}\kappa_{ht2}, \cdots, \eta_K + \sum_{h=1}^{H}\sum_{t=1}^{T}\kappa_{htK}\right)$$

$$\text{where the prior } \eta_k = 3 \text{ for all } k \quad \cdots\cdots\cdots\cdots\cdots\cdots \text{Eq. (3.16)}$$

When the sum of generated κ_{htk} in Eq. (3.16) increases, expected value of s_k also increases as the prior to the Dirichlet distribution increases. In other words, s_k represents the influence of k benefits on the relative magnitude of change within the alternative.

3.3.2 Model specification

The only difference in specification with Kim et al. (2017) benefit-based model is scale parameter as in Eq. (3.17) and Eq. (3.18). Additionally, the assumption that the scale of benefits is also heterogeneous was modeled with Eq. (3.19).

$$u_j = \sum_{k=1}^{K} s_k b_k \left(a_{jk1}, a_{jk2}, ..., a_{jkM_k} \right) + \varepsilon_j \quad \cdots\cdots \text{Eq. (3.17)}$$

$$b_k \left(a_{jk1}, ..., a_{jkM_k} \right) = s_k g_k \left(\sum_{m=1}^{M_k} g_k^{-1} \left(a_{jkm} \right) \right) \quad \cdots\cdots \text{Eq. (3.18)}$$

$$\frac{s_k}{K} \sim Dirichlet_K \left(\eta_1 + \sum_{H,T} \kappa_{ht1}, \cdots, \eta_K + \sum_{H,T} \kappa_{htK} \right) \quad \cdots\cdots \text{Eq. (3.19)}$$

Here, the Dirichlet distribution is a K multivariate continuous probability distribution and is widely used as a prior distribution for Bayesian statistics as a conjugate prior to a categorical distribution (Kotz et al., 2004). Also not that s_k/K is used in Eq. (3.19) instead of s_k. This is to allow range of scale parameter to be zero to K instead of zero to one and thereby provide more parsimonious interpretation. Finally, the proposed DCE model is expressed as Eq. (3.20).

$$u_{hjt} = \sum_{n=1}^{N} \tau^*{}_{n0} \cdot \left(\mathbf{x}'_{hjnt}\boldsymbol{\beta}_{hn}\right) + \sum_{k=1}^{K} s_k \cdot g_k \left(\sum_{n=1}^{N} \tau^*{}_{nk} \cdot g_k^{-1}\left(\mathbf{x}'_{hjnt}\boldsymbol{\beta}_{hn}\right)\right) + \varepsilon_{hjt} \quad \cdots\cdots \text{Eq. (3.20)}$$

3.3.3 Estimation Procedure

Step 1: Set initial values for $\boldsymbol{\beta}_h, \bar{\boldsymbol{\beta}}, \mathbf{V}_\beta, \mathbf{V}_s$ using last 1,000 draws from previous iterations and $s_k = 1$ for all k.

Step 2: Generate $\boldsymbol{\beta}_h$ for *h*=1,2,…,H given $\{s_k\}, \bar{\boldsymbol{\beta}}, \mathbf{V}_\beta$ using random-walk Metropolis Hastings algorithms

$$\text{Draw } \boldsymbol{\beta}_h^{new} \text{ from } N\left(\boldsymbol{\beta}_h^{old}, d^2 \cdot \mathbf{V}_\beta\right), \quad set\, d = 0.3$$

Accept $\boldsymbol{\beta}_h^{new}$ with $\Pr\left(accept\right) = \min\left[1, \dfrac{l_h\left(\boldsymbol{\beta}_h^{new}, \{s_k\}, \{\tau^*_{hn}\} \mid \{z_{hjt}\}\right) \cdot \phi\left(\boldsymbol{\beta}_h^{new} \mid \bar{\boldsymbol{\beta}}, \mathbf{V}_\beta\right)}{l_h\left(\boldsymbol{\beta}_h^{old}, \{s_k\}, \{\tau^*_{hn}\} \mid \{z_{hjt}\}\right) \cdot \phi\left(\boldsymbol{\beta}_h^{old} \mid \bar{\boldsymbol{\beta}}, \mathbf{V}_\beta\right)}\right]$

Step 3: Generate τ^*_{hn} for *n*=1,2,…, N and *h*=1,2,…,H given $\tau^*_{h,-n}, \boldsymbol{\beta}_h, \{\theta_{nk}\}$ following posterior multinomial distribution

$$\tau^*_{hn} \mid \tau^*_{h,-n}, \boldsymbol{\beta}_h, \{\theta_{nk}\} \sim Multinomial_K\left(\tilde{\theta}_{n1}, \tilde{\theta}_{n2}, \cdots, \tilde{\theta}_{nK}\right)$$

$$\text{where } \tilde{\theta}_{nk} = \frac{l_h\left(\tau^*_{hn} = k, \boldsymbol{\beta}_h, \tau^*_{h,-n}\right) \cdot \theta_{nk}}{\sum_{k'=1}^{K} l_h\left(\tau^*_{hn} = k', \boldsymbol{\beta}_h, \tau^*_{h,-n}\right) \cdot \theta_{nk'}}$$

Step 4: Set $\kappa_{htk} = \begin{cases} 1, & if \ \ k = \arg\max\limits_{k'} \left(\text{soft}\max\limits_{j'} \left(g_{htj'k'} \right) \right) \\ 0, & otherwise \end{cases}$ when j' is chosen

Where $\text{soft}\max\limits_{j'} \left(g_{htj'k'} \right) = \exp\left(g_{htj'k'} \right) \Big/ \sum\limits_{j} \exp\left(g_{htjk'} \right)$.

Step 5: Generate $\bar{\boldsymbol{\beta}}, \mathbf{V}_{\beta}$ given $\left\{ \boldsymbol{\beta}_h \right\}$ using Bayesian multivariate regression

$$\boldsymbol{\beta}_h = \bar{\boldsymbol{\beta}} + \varsigma_h, \quad \varsigma_h \sim N\left(0, \mathbf{V}_{\beta}\right)$$

where $\mathbf{V}_{\beta} \sim \text{IW}\left(\text{nvar}+3, \left(\text{nvar}+3\right) \cdot \mathbf{I}_{\text{nvar}}\right)$, $\mathbf{I}_{\text{nvar}} = \text{identity matrix}$

Step 6: Generate $\left\{ \theta_{nk} \right\}$ given τ_{hn}^{*} following posterior Dirichlet distribution

$$\theta_{n0}, \theta_{n1}, \cdots, \theta_{nK} \sim Dirichlet\left(\eta_{n0} + \sum\nolimits_{h=1}^{H} \tau_{hn0}, \eta_{n1} + \sum\nolimits_{h=1}^{H} \tau_{hn1}, \cdots, \eta_{nK} + \sum\nolimits_{h=1}^{H} \tau_{hnK} \right)$$

where the prior $\eta_{nk} = 3$ for all *n*,*k*

Step 7: Generate $\left\{ s_k \right\}$ given κ_{htk} (for *h*=1,2,…,H, *t*=1,2,…,T) following posterior Dirichlet distribution

$$\frac{s_1}{K}, \frac{s_2}{K}, \cdots, \frac{s_K}{K} \sim Dirichlet\left(\eta_1 + \sum_{h=1}^{H}\sum_{t=1}^{T} \kappa_{ht1}, \eta_2 + \sum_{h=1}^{H}\sum_{t=1}^{T} \kappa_{ht2}, \cdots, \eta_K + \sum_{h=1}^{H}\sum_{t=1}^{T} \kappa_{htK} \right)$$

where the prior $\eta_k = 3$ for all *k*

Step 8: repeat step 2 through 7 using MCMC

3.4 Indexed Benefit-scale model

3.4.1 Overview of the Model

In benefit-based model and proposed benefit-scale model, mean of assignment probability $\bar{\theta}_{nk}$ is estimated using last 10,000 iteration data. Author propose model that indexes τ_{nk} =1 for certain value of $\bar{\theta}_{nk}$ and compares model fit with multinomial logit model and benefit-based model. There can be argument about which value of $\bar{\theta}_{nk}$ is appropriate. Author introduce the criteria for indexing τ_{nk}.

Criteria

For *k'* ≥ 1, where $\bar{\theta}_{nk'} \geq 0.5$, set $\tau_{nk'}$ =1.

When there exist no $\bar{\theta}_{nk'} \geq 0.5$ for all *k'*, assign τ_{n0} =1.

For other *k*, set τ_{nk} =0

3.4.2 Estimation Procedure

Model specification is identical to Eq. (3.20) using assumed $\{\tau_{nk}\}$ based on criteria introduced in Section 3.4.1. Estimation procedure is as follows.

Step 1: Set initial values for $\boldsymbol{\beta}_h, \bar{\boldsymbol{\beta}}, \mathbf{V}_\beta, \mathbf{V}_s$ using last 1,000 draws from previous iterations and $s_k = 1$ for all k.

Step 2: Generate $\boldsymbol{\beta}_h$ for *h*=1,2,…,H given $\{s_k\}, \bar{\boldsymbol{\beta}}, \mathbf{V}_\beta$ using random-walk Metropolis Hastings algorithms

$$\text{Draw } \boldsymbol{\beta}_h^{new} \text{ from } N\left(\boldsymbol{\beta}_h^{old}, d^2 \cdot \mathbf{V}_\beta\right), \quad set\, d = 0.3$$

$$\text{Accept } \boldsymbol{\beta}_h^{new} \text{ with } \Pr\left(accept\right) = \min\left[1, \frac{l_h\left(\boldsymbol{\beta}_h^{new}, \{s_k\} \mid \{z_{hjt}\}\right) \cdot \phi\left(\boldsymbol{\beta}_h^{new} \mid \bar{\boldsymbol{\beta}}, \mathbf{V}_\beta\right)}{l_h\left(\boldsymbol{\beta}_h^{old}, \{s_k\} \mid \{z_{hjt}\}\right) \cdot \phi\left(\boldsymbol{\beta}_h^{old} \mid \bar{\boldsymbol{\beta}}, \mathbf{V}_\beta\right)}\right]$$

Step 3: Set $\kappa_{htk} = \begin{cases} 1, \ \ if \ \ k = \arg\max\limits_{k'}\left(\text{soft}\max\limits_{j'}\left(g_{htj'k'}\right)\right) \\ 0, \ \ otherwise \end{cases}$ when j' is chosen

$$\text{Where } \text{soft}\max_{j'}\left(g_{htj'k'}\right) = \exp\left(g_{htj'k'}\right) \Big/ \sum_j \exp\left(g_{htjk'}\right).$$

Step 4: Generate $\bar{\boldsymbol{\beta}}, \mathbf{V}_\beta$ given $\{\boldsymbol{\beta}_h\}$ using Bayesian multivariate regression

$$\boldsymbol{\beta}_h = \bar{\boldsymbol{\beta}} + \varsigma_h, \quad \varsigma_h \sim N\left(0, \mathbf{V}_\beta\right)$$

$$\text{where } \mathbf{V}_\beta \sim \text{IW}\left(\text{nvar}+3, \left(\text{nvar}+3\right) \cdot \mathbf{I}_{\text{nvar}}\right), \quad \mathbf{I}_{\text{nvar}} = \text{identity matrix}$$

Step 5: Generate $\{s_k\}$ given κ_{htk} (for h=1,2,…,H, t=1,2,…,T) following posterior Dirichlet distribution

$$\frac{s_1}{K}, \frac{s_2}{K}, \cdots, \frac{s_K}{K} \sim Dirichlet\left(\eta_1 + \sum_{h=1}^{H} \sum_{t=1}^{T} \kappa_{ht1}, \eta_2 + \sum_{h=1}^{H} \sum_{t=1}^{T} \kappa_{ht2}, \cdots, \eta_K + \sum_{h=1}^{H} \sum_{t=1}^{T} \kappa_{htK} \right)$$

where the prior $\eta_k = 3$ for all k

Step 6: repeat step 2 through 5 using MCMC

3.5 Demographic Indexed Benefit-scale Model

3.5.1 Model Specification

Benefit scale parameter s_k can vary among respondents. Therefore, I introduced γ_h and demographic variable z_h to incorporate differences within respondents model and expressed as Eq. (3.20).

$$u_{hjt} = \sum_{n=1}^{N} \tau^{*}{}_{n0} \cdot \left(\mathbf{x}'_{hjnt} \boldsymbol{\beta}_{hn} \right) + \sum_{k=1}^{K} s_k \left(1 + \sum_{d=1}^{D} \mathbf{z}'_{hd} \boldsymbol{\gamma}_{hd} \right) \cdot g_k \left(\sum_{n=1}^{N} \tau^{*}{}_{nk} \cdot g_k^{-1} \left(\mathbf{x}'_{hjnt} \boldsymbol{\beta}_{hn} \right) \right) + \varepsilon_{hjt} \qquad \cdots\cdots\cdots\cdots \text{Eq. (3.20)}$$

3.5.2 Estimation Procedure

$\{\tau_{nk}\}$ is assumed following criteria introduced in Section 3.4.1.

Step 1: Set initial values for $\boldsymbol{\beta}_h, \bar{\boldsymbol{\beta}}, \boldsymbol{\gamma}_h, \bar{\boldsymbol{\gamma}}, \mathbf{V}_\beta, \mathbf{V}_\gamma$ using last 1,000 draws from previous iterations and $s_k = 1$ for all k.

Step 2: Generate $\boldsymbol{\beta}_h, \boldsymbol{\gamma}_h$ for h=1,2,…,H given $\{s_k\}, \bar{\boldsymbol{\beta}}, \bar{\boldsymbol{\gamma}}, \mathbf{V}_\beta, \mathbf{V}_\gamma$ using random-walk Metropolis Hastings algorithms

$$\text{Draw } \boldsymbol{\beta}_h^{new} \text{ from } N\left(\boldsymbol{\beta}_h^{old}, d^2 \cdot \mathbf{V}_\beta\right), \quad set\, d = 0.3$$

$$\text{Draw } \boldsymbol{\gamma}_h^{new} \text{ from } N\left(\boldsymbol{\gamma}_h^{old}, d^2 \cdot \mathbf{V}_\gamma\right), \quad set\, d = 0.3$$

$$\text{Accept } \boldsymbol{\beta}_h^{new},\ \boldsymbol{\gamma}_h^{new} \text{ with}$$

$$\Pr\left(accept\right) = \min\left[1, \frac{l_h\left(\boldsymbol{\beta}_h^{new}, \boldsymbol{\gamma}_h^{new}\left\{s_k\right\} \mid \left\{z_{hjt}\right\}\right) \cdot \phi\left(\boldsymbol{\beta}_h^{new}, \boldsymbol{\gamma}_h^{new} \mid \overline{\boldsymbol{\beta}}, \mathbf{V}_\beta\right)}{l_h\left(\boldsymbol{\beta}_h^{old}, \boldsymbol{\gamma}_h^{old}, \left\{s_k\right\} \mid \left\{z_{hjt}\right\}\right) \cdot \phi\left(\boldsymbol{\beta}_h^{old}, \boldsymbol{\gamma}_h^{old} \mid \overline{\boldsymbol{\beta}}, \mathbf{V}_\beta\right)}\right]$$

Step 3: Set $\kappa_{htk} = \begin{cases} 1, & if\ \ k = \arg\max\limits_{k'}\left(\operatorname{soft}\max\limits_{j'}\left(g_{htj'k'}\right)\right) \\ 0, & otherwise \end{cases}$ when j' is chosen

Where $\operatorname{soft}\max\limits_{j'}\left(g_{htj'k'}\right) = \exp\left(g_{htj'k'}\right) \Big/ \sum_j \exp\left(g_{htjk'}\right)$.

Step 4: Generate $\overline{\boldsymbol{\beta}}, \overline{\boldsymbol{\gamma}}, \mathbf{V}_\beta, \mathbf{V}_\gamma$ given $\left\{\boldsymbol{\beta}_h, \boldsymbol{\gamma}_h\right\}$ using Bayesian multivariate regression

$$\boldsymbol{\beta}_h = \overline{\boldsymbol{\beta}} + \varsigma_h, \quad \varsigma_h \sim N\left(0, \mathbf{V}_\beta\right),$$

$$\boldsymbol{\gamma}_h = \overline{\boldsymbol{\gamma}} + \zeta_h, \quad \zeta_h \sim N\left(0, \mathbf{V}_\gamma\right)$$

$$\text{where } \mathbf{V}_\beta \sim \mathrm{IW}\left(\mathrm{nvar}+3, \left(\mathrm{nvar}+3\right) \cdot \mathbf{I}_{\mathrm{nvar}}\right),$$

$$\mathbf{V}_\gamma \sim \mathrm{IW}\left(\mathrm{nvar}+3, \left(\mathrm{nvar}+3\right) \cdot \mathbf{I}_{\mathrm{nvar}}\right),$$

$$\mathbf{I}_{\mathrm{nvar}} = \text{ identity matrix}$$

Step 5: Generate $\left\{s_k\right\}$ given κ_{htk} (for h=1,2,…,H, t=1,2,…,T) following posterior Dirichlet distribution

$$\frac{s_1}{K}, \frac{s_2}{K}, \cdots, \frac{s_K}{K} \sim Dirichlet\left(\eta_1 + \sum_{h=1}^{H}\sum_{t=1}^{T}\kappa_{ht1}, \eta_2 + \sum_{h=1}^{H}\sum_{t=1}^{T}\kappa_{ht2}, \cdots, \eta_K + \sum_{h=1}^{H}\sum_{t=1}^{T}\kappa_{htK}\right)$$

where the prior $\eta_k = 3$ for all k

Step 6: repeat step 2 through 5 using MCMC

Chapter 4. Empirical Studies

4.1 The Study on OTT services

4.1.1 Introduction

In January 2016, Netflix, a leading global OTT provider, surprised the industry by announcing 130+ simultaneous launches in new countries and regions including Korea. As of May 2020, Netflix has launched service in more than 190 countries around the world in the pandemic situation with 193 million subscribers, of which about 60% are from countries outside the United States (Comparitech, 2020).

OTT services are rapidly penetrating in Korea, and according to Lee (2020), 52% of them used OTT as of 2019, and the OTT usage rate has steadily increased over the past three years[4]. In addition, the proportion of using TV as a OTT service watching device has increased by about twice over a year, and the proportion of OTT watching on TV is now larger than that of PC[5].

The market opportunity has rapidly increased, but competition is intensifying as various companies enter the market. In this situation, we want to understand which OTT service consumers prefer, and which attributes are likely to be grouped in a benefit, and derive managerial implications.

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[4] Usage rate of OTT service in Korea 2017, 36.1%; 2018, 42.7%; 2019, 52.0%
[5] Usage of TV as OTT watching device in Korea 2018, 2.4%; 2019, 5.4%

4.1.2 Data

In this study, DCE was used to analyze the preference for OTT, and data was acquired through a face to face offline questionnaire. The survey for this study was conducted in eight major cities including Seoul, the capital city where about half of the Korean population resides through the Gallup Korea Research Institute, which is a specialized survey organization. 665 respondents aged 20 to 60 were selected considering the understanding of the OTT service survey. The survey period was conducted for 3 weeks from June 28 to July 18, 2019, and Purposive-quota sampling was used as the sampling method based on region, sex, and age. The sample demographic characteristics including the allocation criteria are shown in Table 1 below.

Table 1. Demographic characteristics of respondents: OTT data

Group		No. of Respondents	Component Ratio (%)
Total		665	100.0
Sex	Male	337	50.7
	Female	328	49.3
Age	20 to below 30	152	22.9
	30 to below 40	160	24.1
	40 to below 50	177	26.6
	50 to below 60	176	26.5
Region	Seoul	271	40.8
	Busan	91	13.7
	Incheon	85	12.8
	Daegu	69	10.4
	Gwangju	42	6.3

	Daejeon	41	6.2
	Kyunggi new town	66	9.9
Education Level*	High school graduates or lower	238	35.8
	College students or higher	426	64.1

* 1 no response

In this study, eight attributes in OTT service attributes were set, and all other attributes constituting OTT service were assumed to be identical. Eight attributes were designed based on issues previously discussed in the existing literature.

Shin et al. (2016) conducted a conjoint experiment based on five attributes (price, livestream, number of VODs, up to date VODs, terrestrial broadcasting service provided) to investigate the preference of OTT services in Korea. Kim et al. (2017b) performed conjoint analysis by selecting four competitive factors (recommendation system, maximum resolution, live streaming and download availability, price) promoted by OTT operators as attributes. Table 2. shows the attributes and levels of OTT service used in this DCE and their description.

Based on the attributes that are importantly discussed in the existing OTT service literatures, the number of attributes is set to eight, and it is assumed that all other attributes constituting the OTT service equal.

Table 2. Discrete choice experiment's attribute, level and description: OTT service

Attribute	Level	Description

Service provider	Telecommunication service provider	The telecommunication service provider provides the same real-time channel and VOD service of the existing IPTV in the OTT service. (Example: SKT oksusu, KT Olleh TV Mobile, LG U+ TV)
	Broadcasting company	Broadcasting companies provide their own content by developing OTT services independently by terrestrial/program provider/cable TV operators. (Example: POOQ, TVING)
	Platform operators	Platform operators provide their own services through the Internet by video platform operators. (Example: Netflix, Watcha Play, NaverTV, KakaoTV, etc.)
Contents	100% 70% 40%	Diversity of content provided by paid OTT services based on the number of content provided by IPTV. Therefore, the attribute level refers to the ratio of the number of paid broadcasting service contents.
Resolution	HD FHD UHD	UHD and Full HD are 8x and 2x HD, respectively, with screen clarity and resolution levels.
Viewable form	VOD only VOD + download VOD + download + livestream	How you can watch the broadcast programs or contents you want. VOD streaming refers to the ability to view the content again as streaming. Download capability allows you to download content over the Internet and watch it later without consuming data. And live streaming refers to the ability to watch live broadcasts over the Internet or through data consumption.
Viewable devices	Mobile only Mobile + PC Mobile+PC+Smart TV	The type and number of devices available when subscribing to paid OTT service (one user can watch on multiple devices)
Simultaneous viewing	Provided None	Multiple people can watch at the same time on multiple devices with one paid account (multiple people can create multiple profiles in one account and watch contents independently)
Exclusive contents	Provided None	Means whether or not content that can be viewed only on the platform is provided (eg, Netflix original movie 'Okja', exclusive live broadcast on POOQ World Cup mobile, live broadcast of Naver V Live idol, etc.)
Price	6,000 won/month 10,000 won/month 14,000 won/month	Monthly fee paid for using the paid OTT service.

This study composed a total of 24 alternatives through orthogonal design, one of fractional factorial designs. And 24 alternatives were classified into 8 choice sets, 3 each and presented to respondents. The following Table 3. is an example of the choice set used in the study. In the survey process, additional explanations for the level of attributes that are not familiar with the respondents were provided in detail.

Table 3. Example of choice set: OTT service

Attribute	Type A	Type B	Type C
Service provider	Platform	Platform	Broadcasting
Contents	100%	70%	70%
Resolution	FHD	UHD	HD
Viewable form	VOD + download + livestream	VOD + download	VOD + download + livestream
Viewable devices	Mobile + PC	Mobile + PC + Smart TV	Mobile + PC + Smart TV
Simultaneous viewing	Provided	None	Provided
Exclusive contents	Provided	Provided	None
Price	10,000 won	14,000 won	14,000 won
Choice	Type A	Type B	Type C

4.1.3 MNL & Benefit-based(BB) Model: Estimation Results

In the benefit based model, in order to determine which attributes are probabilistically grouped into a benefit group, K values are previously set by researchers and then estimated. Optimal number of benefit group, K is derived by looking at the fit statistic (Kim et al., 2017). In this study, after running 20,000 iterations of Marcov Chain Monte Carlos (MCMC) for each K, only the 10th data of the last 10,000 data were extracted and used in deriving the log-marginal density (LMD) [6]. A total of 1,000 values were used for derivation. LMD and In-sample hit rate and hit probability is highest for K=2, but holdout sample model fit is best when K=3. I used K=2 as a base model to provide parsimonious interpretation.

Table 4. Fit Statistics (MNL & Benefit-based model): OTT Data

		In-sample		Holdout sample	
Models	LMD	Hit rate	Hit prob.	Hit rate	Hit prob.
Multinomial Logit (K=0)	-2020.432	0.790	0.762	0.530	0.528
Benefit-based Model (K=1)	-1902.103	0.815	0.745	0.559	0.540
Benefit-based Model (K=2)	-1816.836	0.834	0.768	0.582	0.564
Benefit-based Model (K=3)	-1903.859	0.823	0.753	0.585	0.565

Looking at LMD and predictive statistic in Table 4., it can be seen that the benefit-based model is more appropriate than the standard multinomial logit model (K=0). Note

[6] Newton–Raftery(1994) method was used to calculate LMD.

that K=0 is identical to multinomial logit with individual heterogeneity as it does not exhibit any nested satiation structure in utility. To see the predictive fit statistic, this dissertation empirically analyzed data consisting of eight choice tasks. In this study, the procedure of verifying the model with data generation process is not performed[7].

In the benefit based model, the assignment probability is a random variable with Dirichlet distribution that the sum is 1. Estimated value of assignment probability is in Table 5. The figures displayed in bold are those with an assignment probability of 0.5 or more within each attribute. At K=1, all attribute assignment probabilities were higher than 0.5 which mean it is more appropriate to use nested satiation structure as benefit rather than multinomial logit and thereby diminishing marginal utility applies to the data.

At K=2, benefit grouping was done to some extent, but it cannot be said that it was clearly achieved. Among them, the most obviously grouped attributes were the contents and price attributes. In other attributes, the result of grouping that is not clear.

[7] About data generation process, see Kim et al. (2017).

Table 5. Posterior Estimates of Assignment Probabilities θ_{nk} : OTT Data

	K=1		K=2			K=3			
Attributes	Null	Benefit1	Null	Benefit1	Benefit2	Null	Benefit1	Benefit2	Benefit3
telecom	**0.53**	0.47	0.22	0.48	0.30	0.22	0.26	0.24	0.27
platform	**0.51**	0.49	0.37	0.36	0.27	0.23	0.25	0.25	0.26
contents	0.11	**0.89**	0.13	0.31	**0.55**	0.16	0.26	0.30	0.27
FHD	0.24	**0.76**	0.24	0.40	0.37	0.20	0.30	0.24	0.26
UHD	0.27	**0.73**	0.22	0.43	0.34	0.19	0.25	0.28	0.28
download	0.21	**0.79**	0.27	0.34	0.39	0.24	0.24	0.26	0.26
livestream	0.10	**0.90**	0.19	0.44	0.37	0.19	0.26	0.29	0.25
PC	0.29	**0.71**	0.28	0.37	0.35	0.25	0.25	0.26	0.24
TV	0.29	**0.71**	0.18	0.42	0.40	0.22	0.25	0.27	0.26
simview	0.22	**0.78**	0.23	0.35	0.42	0.23	0.25	0.26	0.25
exclusive	0.20	**0.80**	0.15	0.46	0.39	0.20	0.26	0.26	0.27
price	0.29	**0.71**	0.18	0.28	**0.54**	0.22	0.27	0.25	0.26

Table 5. shows the assignment probability for each attribute. At K=3, the assignment probability for all attribute was near 1/(K+1), indicating that it was not grouped to specific benefit. At K=2, contents and price are likely to be satiated when attributes are considered directly together by respondents.

In Table 6, parameter estimates of standard multinomial logit(K=0) and benefit based model are presented. Signs of parameter estimate for K=2 are equal with K=0 (standard multinomial logit) and estimates $\bar{\beta}$ itself does not differ significantly.

Table 6. Posterior estimates of the $\bar{\beta}$ (MNL and Benefit-based model): OTT Data

Variables	K=0 (MNL)	K=1	K=2	K=3
telecom	0.731	0.229	0.096	0.164
	(0.536)	(0.199)	(0.192)	(0.236)
platform	1.083	0.826	0.744	0.738
	(0.254)	(0.375)	(0.249)	(0.270)
contents	2.510	3.494	3.807	3.414
	(0.352)	(0.254)	(0.210)	(0.263)
FHD	-0.072	0.375	0.908	1.060
	(0.391)	(0.398)	(0.315)	(0.339)
UHD	0.518	1.121	1.672	1.581
	(0.515)	(0.267)	(0.466)	(0.362)
download	1.520	1.283	1.182	0.984
	(0.216)	(0.521)	(0.298)	(0.349)
livestream	1.471	2.577	1.945	1.410
	(0.435)	(0.346)	(0.373)	(0.321)
PC	1.566	1.377	2.068	1.865
	(0.229)	(0.265)	(0.226)	(0.344)
TV	0.833	1.116	2.095	1.439
	(0.470)	(0.332)	(0.358)	(0.158)
simview	0.764	2.044	1.908	1.296
	(0.519)	(0.303)	(0.295)	(0.231)
exclusive	-0.183	1.206	1.139	0.499
	(0.374)	(0.528)	(0.335)	(0.248)
price	-4.893	-4.527	-4.314	-4.470
	(0.905)	(0.371)	(0.316)	(0.400)

Notes: Standard deviation in parenthesis.

Comparing estimated $\bar{\beta}$ at K=0 and K=2 by box plot is as shown in figure 9. It can be seen that the standard deviation was reduced for all attributes except Livestream, resulting in a more significant estimate.

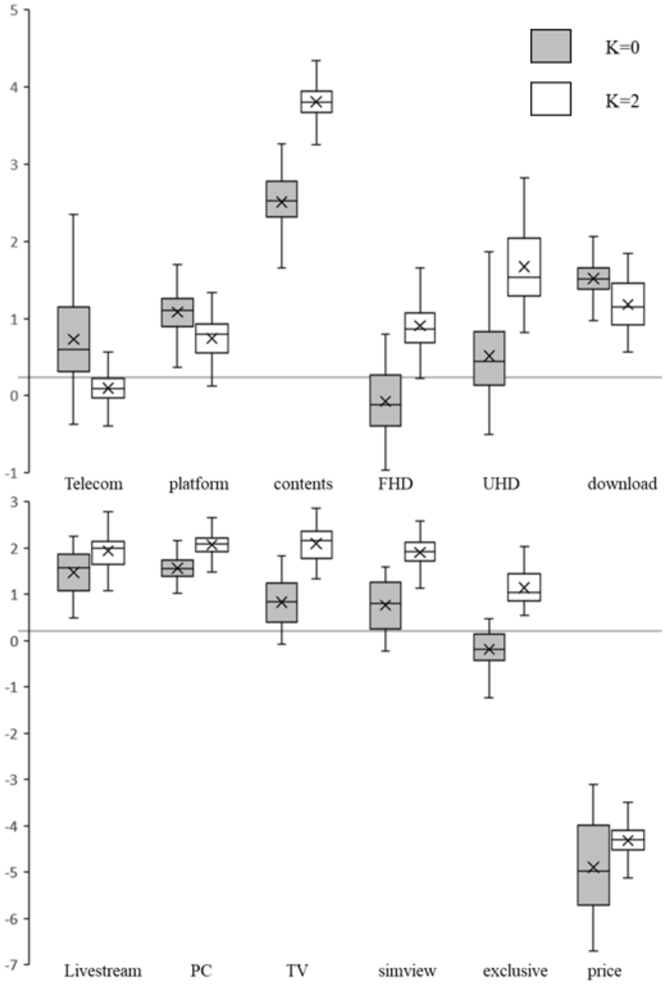

Figure 10. Comparison of $\bar{\beta}$ for MNL and BB model: OTT data

Interpretation of the estimated $\bar{\beta}$ using benefit-based model is identical to multinomial logit model(MNL) except for viewable device option and is as follows:

Service provider

Consumers prefer the case where the OTT service provider is the platform operator than the case where the OTT service provider is a communication service provider or a broadcasting service provider.

Image quality

The maximum image quality provided by the OTT service showed higher preference when it was FHD or UHD or higher than HD

Viewing option

Consumer prefers an additional download function and livestreaming functions rather than only VOD service.

Viewable device option

Consumers preferred the option to watch the contents on PC or smart-TV rather than mobile-only. Although the magnitude is not significant, the attribute level that can be viewed through mobile, PC, and smart TV is more preferred than attribute level that can be viewed using only mobile and PC in benefit-based model but not in multinomial logit model(K=0).

Simultaneous viewing option

In addition, when providing a function that allows simultaneous viewing on multiple devices with a single paid account.

Exclusive content

Preference for the OTT service increased when exclusive content is provided.

4.1.4 Satiation in Utility(SU) Model: Estimation Results

Model fit statistic of satiation in utility (SU) model is compared with standard multinomial logit (MNL), benefit-based (BB) model in Table 7. SU model showed best predictive fit for holdout sample, but lowest explanatory power for in-sample data. Satiation in OTT service data seems to increase predictive power. Table 7. confirms that satiation does not occur only at the benefit level, but can also occur at the overall utility level.

Table 7. Fit Statistics (MNL, BB & SU model): OTT Data

		In-sample		Holdout sample	
Models	LMD	Hit rate	Hit prob.	Hit rate	Hit prob.
Multinomial Logit Model	-2020.432	0.790	0.762	0.530	0.528
Benefit-based Model	-1816.836	0.834	0.753	0.582	0.565
Satiation in utility Model	-2221.497	0.765	0.689	0.608	0.572

Parameter estimates of standard multinomial logit (MNL) and satiation in utility (SU) model are presented in Table 8. Signs of parameter estimate did not differ significantly between MNL and SU model. Comparing estimated $\bar{\beta}$ at K=0 and K=2 by box plot is as shown in Figure 12.

Table 8. Posterior estimates of the $\bar{\beta}$ (MNL and SU model): OTT Data

Variables	MNL	Satiation in utility(SU)
telecom	0.731	1.050
	(0.536)	(0.519)
platform	1.083	-0.052
	(0.254)	(0.288)
contents	2.510	2.566
	(0.352)	(0.210)
FHD	-0.072	1.774
	(0.391)	(0.294)
UHD	0.518	0.933
	(0.515)	(0.558)
download	1.520	-0.373
	(0.216)	(0.408)
livestream	1.471	1.746
	(0.435)	(0.548)
PC	1.566	1.055
	(0.229)	(0.964)
TV	0.833	1.039
	(0.470)	(0.287)
simview	0.764	0.878
	(0.519)	(0.174)
exclusive	-0.183	1.368
	(0.374)	(0.280)
price	-4.893	-3.771
	(0.905)	(0.238)

Notes: Standard deviation in parenthesis.

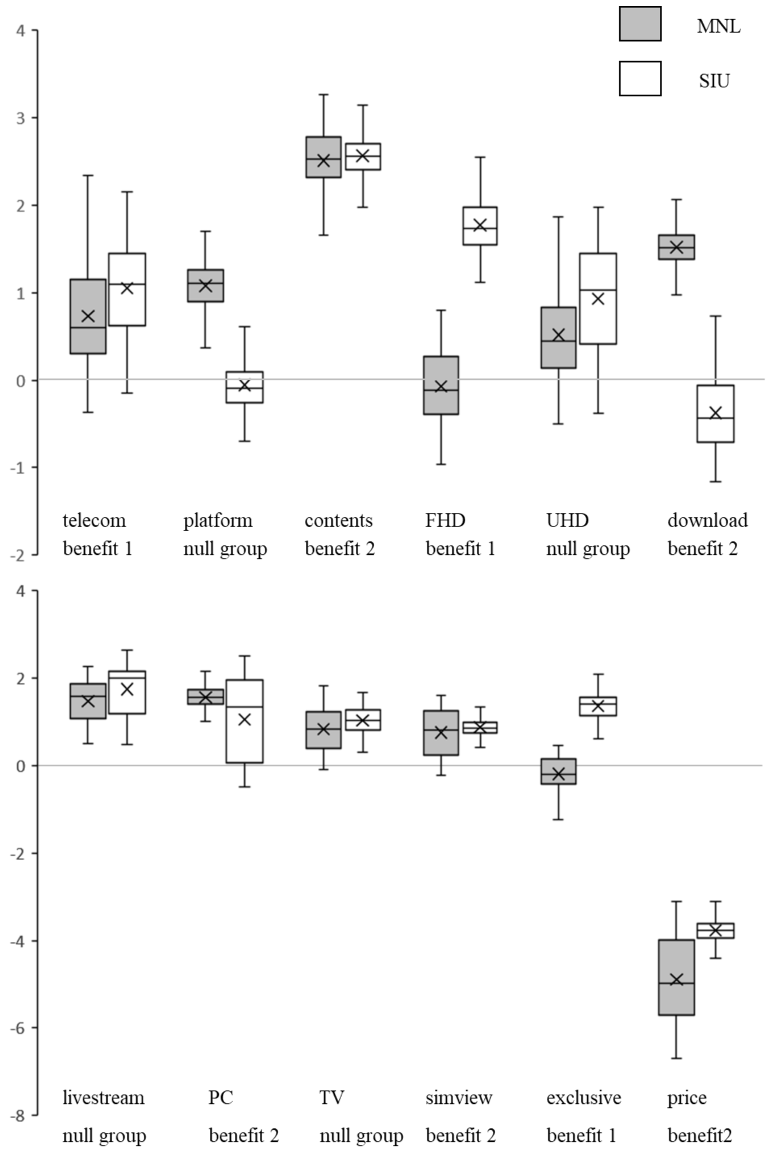

Figure 11. Comparison of $\bar{\beta}$ for MNL and SU model: OTT data

4.1.5 Benefit-scale(BS) Model: Estimation Results

As shown in Section 4.1.3, the Base K=2 model did not exhibit benefit grouping with probability assignment. I compared fit statistic among multinomial logit model(K=0), benefit-based model(K=2) and proposed benefit-scale model(K=2) in Table 9. In section 4.1.4, I presented estimated results which yielded highest model fit with respect to holdout sample hit rate and hit probability. I attach Appendix 2 for additional iteration results to see if there exists other local solutions.

Table 9. Fit Statistics (MNL, Benefit-based & Benefit-scale model): OTT Data

		In-sample		Holdout sample	
Models	LMD	Hit rate	Hit prob.	Hit rate	Hit prob.
Multinomial Logit Model	-2020.432	0.790	0.762	0.530	0.528
Benefit-based Model	-1816.836	0.834	0.753	0.582	0.565
Benefit-scale Model	-212.176	0.931	0.913	0.613	0.611

Assignment Probability

Table 10. shows estimated assignment probability (θ_{nk}) and each benefit group's scale parameter (s_k). Bold indicates assignment probability of 0.5 or higher. Author also presents discussion on sensitivity of scale parameter when prior of the Dirichlet distribution differs from three on Appendix 3.

Table 10. Posterior Estimates of Assignment Probabilities θ_{nk} (BB & BS) : OTT Data

	Benefit-base Model			Benefit-scale Model		
Attributes	Null	Benefit1	Benefit2	Null	Benefit1	Benefit2
telecom	0.22	0.48	0.30	0.24	**0.63**	0.13
platform	0.37	0.36	0.27	**0.57**	0.23	0.20
contents	0.13	0.31	**0.55**	0.12	0.12	**0.76**
FHD	0.24	0.40	0.37	0.15	**0.57**	0.28
UHD	0.22	0.43	0.34	0.35	0.18	0.46
download	0.27	0.34	0.39	0.26	0.09	**0.65**
livestream	0.19	0.44	0.37	**0.64**	0.12	0.24
PC	0.28	0.37	0.35	0.19	0.24	**0.58**
TV	0.18	0.42	0.40	0.32	0.18	0.49
simview	0.23	0.35	0.42	0.09	0.12	**0.79**
exclusive	0.15	0.46	0.39	0.37	**0.51**	0.12
price	0.18	0.28	**0.54**	0.07	0.04	**0.90**
s_k		1.00	1.00		1.429	0.572

Introduction of scale parameter (s_k) clearly enhances attribute to benefit group assignment probability (θ_{nk}) convergence as seen in Table 8. Clear grouping of attributes price and contents is achieved in both the benefit-based model and the benefit-scale model. For benefit-scale model, attributes download, PC, and simview were grouped together with contents and price as benefit 2.

When certain attribute's assignment probability for a specific group is 0.5 or higher, I interpreted as it to be assigned to that group. When there exists no assignment probability of 0.5 or higher for certain attribute, it is assumed to be assigned to a null group. This grouping is summarized in Table 9. Content diversity within the OTT service (contents), price, PC viewing option (PC), simultaneous viewing (simview) attributes are likely to be grouped as benefit 1, and attributes communication service provider (telecom), FHD image quality (FHD), exclusive content (exclusive) are likely to be grouped as benefit 2.

Table 11. Attribute to benefit grouping: OTT data

Benefit group (k)	Attributes (n)	Remark
Null group	platform, UHD, livestream, TV	
Benefit 1	telecom, FHD, exclusive	Telecom related
Benefit 2	contents, download, PC, simview, price	IPTV related

Remark of benefit group

In Table 11, author also specified the representative characteristic of the benefit group as a remark. Additional procedure of Focus Group Interview (FGI) may be required as in the study of Kim et al. (2017), but author believe that it is reasonable to interpret the result as in remark as it provides interpretation of grouping.

Null group

Attributes grouped in null group has important implication for OTT service designers and planners. These attributes do not satiate with other attribute(s) and deliver unique utility to consumers. It is important for OTT service providers to provide UHD as image quality, livestream content and TV as a viewable option.

Table 12. Posterior estimates of the $\bar{\beta}$ (MNL & BS model): OTT Data

Variables	K=0 (MNL)	Benefit-scale model (K=2)
telecom	0.731	2.124
	(0.536)	(2.199)
platform	1.083	0.699
	(0.254)	(0.731)
contents	2.510	13.596
	(0.352)	(5.607)
FHD	-0.072	1.627
	(0.391)	(2.184)
UHD	0.518	1.629
	(0.515)	(2.448)
download	1.520	2.706
	(0.216)	(1.990)
livestream	1.471	2.506
	(0.435)	(1.722)
PC	1.566	3.709
	(0.229)	(1.303)
TV	0.833	1.316
	(0.470)	(1.348)
simview	0.764	7.427
	(0.519)	(2.385)
exclusive	-0.183	0.684
	(0.374)	(0.385)
price	-4.893	-42.858
	(0.905)	(28.367)

Notes: Standard deviation in parenthesis.

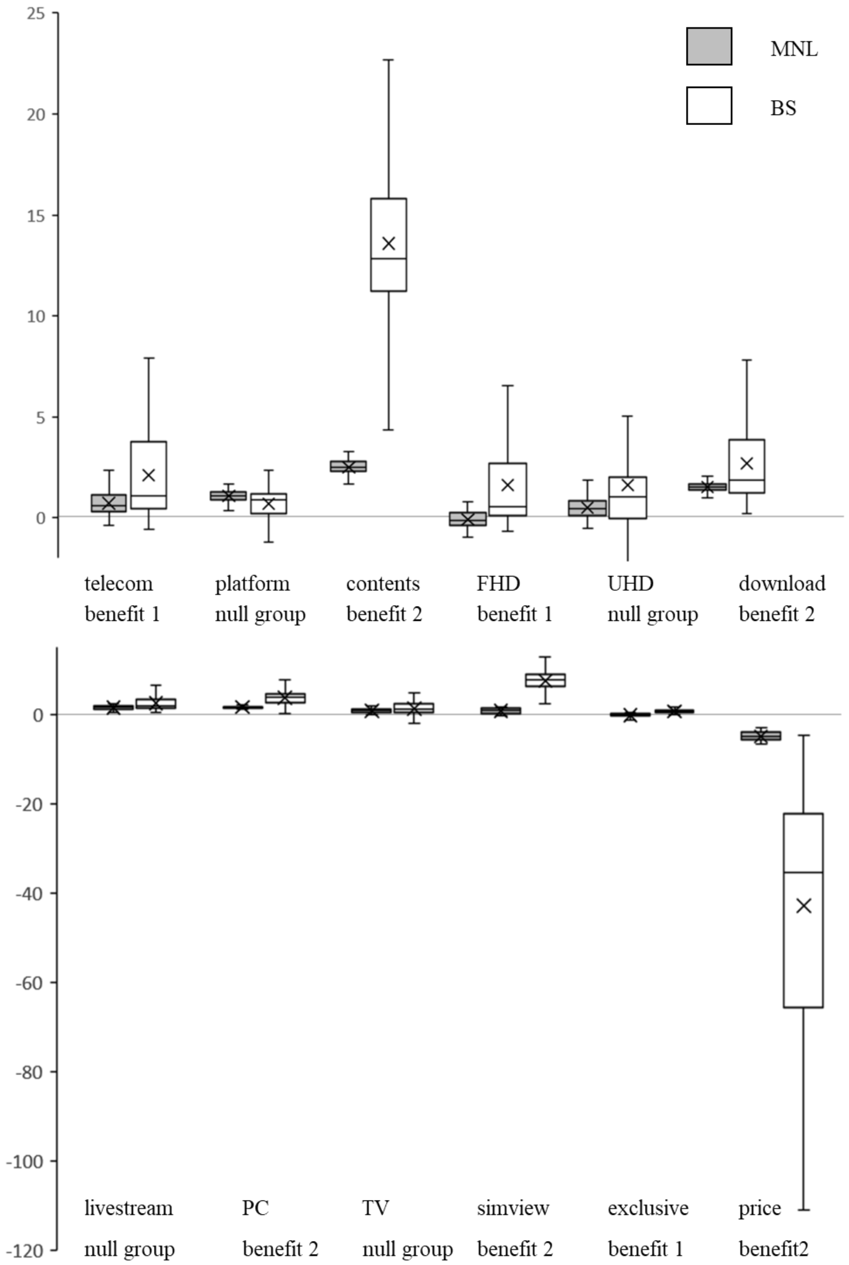

Figure 12. Comparison of $\bar{\beta}$ for MNL and BS model: OTT data

Parameter estimates

In Table 12, it can be seen that the positive and negative sign directions of the MNL model and the benefit-scale model is same, but the magnitude of the magnitude is very different. This is due to the introduction of the scale parameter. For a benefit with a relatively large (small) scale parameter, the estimate is derived to be small (large) in magnitude. Unlike the benefit-based model, when comparing the magnitude, appropriate comparisons are possible only between attributes belonging to the same benefit (attributes within benefit), which is a disadvantage of benefit-scale model that makes interpretation difficult.

Within Benefit Interpretation

As explained in the model, attributes within the benefit are satiated. In other words, if multiple attributes with (dis)utility are provided in a benefit, the marginal (dis)utility decreases according to the law of diminishing marginal (dis)utility.

Based on this, the interpretation of Benefit 1 is as follows. If the OTT service is provided by the telecommunication company providing FHD quality, the utility is likely to satiate, whereas if UHD quality is provided, the utility is not likely to satiate. Also, if a telecommunications company provides exclusive content, the utility is likely to be satiated. Whereas if other OTT service operators provide exclusive content, the utility is not likely to be satiated. This might be due to the fact that consumers are expecting to transmit UHD image quality by utilizing the strengths of infrastructure such as servers owned by telecommunications operators, and telecommunications companies expecting that they will not have the ability to produce excellent exclusive contents.

For benefit 2, content diversity and price is highly likely to have direct trade-off relationship within benefit as it is estimated to have the highest assignment probability in benefit 2. When it comes to viewing device options, it satiates when it can be viewed on a PC, but the satiation probability is smaller when viewing on a smart TV is also possible. The less the diversity of contents, the less satiation occurs for providing a PC as a viewing device option. In addition, consumers believe that PC as a viewing option is likely to be optional. This may be due to an example presented in DCE as an OTT service provided by a IPTV or cable SO. The examples presented were POOQ and TVING, and the price was 6,900 won/month, which was cheaper than other OTT services. Note that baseline for service provider was IPTV or cable SO. This OTT service is an OTT service that allows users to view content provided on IPTV on mobile, targeting customers who are already using IPTV or cable TV. It is a service that allows you to watch TV while on the go. This can be interpreted that it is possible to view that providing other viewable devices other than mobile devices is unnecessary in the OTT service provided by the IPTV or cable SO.

Implications

When IPTV of cable SO provides an OTT service, it can be said that consumers perceive the OTT service as an additional service derived from an existing IPTV or cable TV, and considers the situation that he(or she) is already subscribing IPTV or cable TV service. On the other hand, when a telecommunications service provider provides OTT service, the utility from providing exclusive content is satiated, and consumers expect UHD in image quality.

Implications for IPTV or cable TV SO

These results provide an interpretation that when IPTV or cable TV SO provide OTT services, they should provide content diversity comparable to that of existing IPTV while providing low prices. When IPTV or cable TV SO provides OTT service, they should provide content diversity that is comparable to that of existing IPTV, and the price as low as 6,000 won/month.

Also, providing download, simultaneously watching and watching on PC option is preferable but the utility from additional options satiate. Therefore, taking satiation in considerable, when IPTV or cable TV SO provides OTT service, providing the attribute belonging to the null group will help to target more consumers. Also, the result that providing image quality of FHD or higher or providing exclusive content did not provide great utility should be taken into consideration.

However, IPTV or cable TV SO should be careful about carnivalization in providing attributes belonging to the null group. Providing livestreaming or viewing option on a smart TV clearly provides utility that do not satiate, but it is important to note that improved OTT service will function exactly the same (or even better, as it can be watched on mobile device and much more devices conditional to options provided) than existing IPTV of cable TV service. Consumers might show cord-cutting behavior of only subscribing OTT service and unsubscribing IPTV or cable TV service.

4.1.6 Indexed Benefit-scale(IBS) Model: Estimation Results

Model specification is identical to Eq. (3.20), which is benefit-scale model using assumed $\{\tau_{nk}\}$ based on criteria introduced in Section 3.4.1. As can be seen in Table 13, IBS model did not provide significantly higher fit statistics, but shown similar model fit statistic as MNL.

Although IBS model fit statistics showed no improvement than MNL, it is meaningful in itself that it has a fit statistic similar to MNL. IBS model enables further interpretation of the estimation results but cautious approach is required as IBS model utilizes strong assumption that the assignment probability is identical for all respondents *h*.

Table 13. Fit Statistics (MNL, Benefit-based & Indexed Benefit-scale model): OTT Data

		In-sample		Holdout sample	
Models	LMD	Hit rate	Hit prob.	Hit rate	Hit prob.
Multinomial Logit Model	-2020.432	0.790	0.762	0.530	0.528
Benefit-based Model	-1816.836	0.834	0.753	0.582	0.565
Indexed Benefit-scale Model	-1823.109	0.822	0.756	0.535	0.523

Parameter Estimates

Parameter estimates of standard multinomial logit (MNL) and IBS model are presented in Table 14. and Figure 13. Signs of parameter estimate except download attribute did not differ significantly between MNL and IBS model.

Table 14. Posterior estimates of the $\bar{\beta}$ (MNL & IBS model): OTT Data

Variables	Multinomial Logit	Indexed BS model (K=2)
telecom	0.731	-0.099
	(0.536)	(0.248)
platform	1.083	0.893
	(0.254)	(0.306)
contents	2.510	3.331
	(0.352)	(0.295)
FHD	-0.072	0.174
	(0.391)	(0.498)
UHD	0.518	0.135
	(0.515)	(0.512)
download	1.520	-0.711
	(0.216)	(0.377)
livestream	1.471	0.291
	(0.435)	(0.154)
PC	1.566	3.091
	(0.229)	(0.310)
TV	0.833	0.58
	(0.470)	(0.276)
simview	0.764	2.504
	(0.519)	(0.365)
exclusive	-0.183	0.249
	(0.374)	(0.133)
price	-4.893	-4.083
	(0.905)	(0.504)

Notes: Standard deviation in parenthesis.

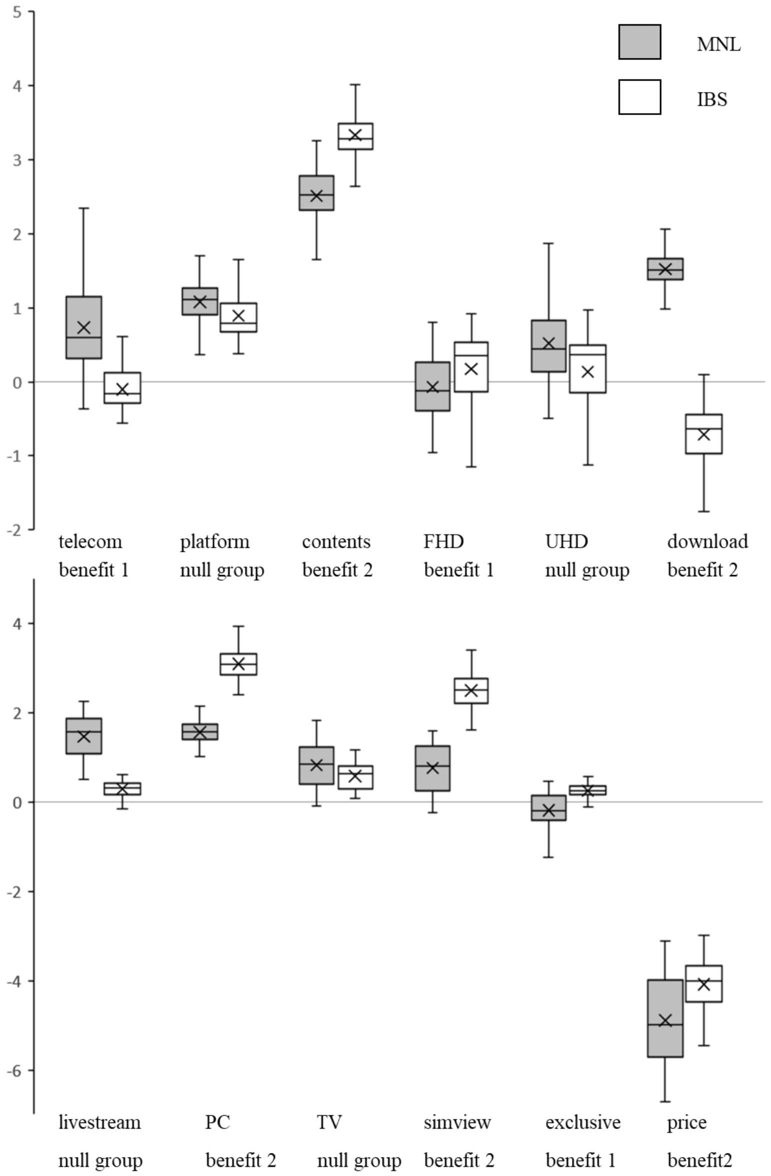

Figure 13. Comparison of $\bar{\beta}$ for MNL and IBS: OTT data

4.1.7 Demographic Indexed Benefit-scale(DIBS) Model: Results

Model specification is described in Eq. (3.20). For demographic variables, sex and age is used. Introducing demographic variable in scale parameter increased model fit statistics as shown in Table 15. However, a careful approach is needed to generalize and introduce these variables as degree of freedom increases in the model as variables are added. Also, it should be noted that demographic variables are added to IBS model, not BS model.

Table 15. Fit Statistics (IBS & DIBS model): OTT Data

		In-sample		Holdout sample	
Models	LMD	Hit rate	Hit prob.	Hit rate	Hit prob.
Indexed Benefit-scale Model	-1823.109	0.822	0.756	0.535	0.523
Demographic IBS Model	-1658.906	0.833	0.782	0.544	0.534

Demographic Variables

Study used sex and age as demographic variable to investigate heterogeneity in scale parameter. From estimated result, γ_{male} and γ_{age} were 0.287 and 0.323 respectively. Which indicates that women and younger individuals consider the unique attribute more important.

Table 16. Posterior estimates of the $\bar{\beta}$ (MNL & DIBS model): OTT Data

Variables	Multinomial Logit (MNL)	DIBS model (K=2)
telecom	0.731	0.034
	(0.536)	(0.033)
platform	1.083	0.049
	(0.254)	(0.019)
contents	2.510	0.203
	(0.352)	(0.080)
FHD	-0.072	0.061
	(0.391)	(0.027)
UHD	0.518	-0.09
	(0.515)	(0.035)
download	1.520	0.173
	(0.216)	(0.043)
livestream	1.471	0.085
	(0.435)	(0.018)
PC	1.566	0.303
	(0.229)	(0.071)
TV	0.833	-0.094
	(0.470)	(0.014)
simview	0.764	0.228
	(0.519)	(0.078)
exclusive	-0.183	-0.088
	(0.374)	(0.023)
price	-4.893	-0.654
	(0.905)	(0.169)

Notes: Standard deviation in parenthesis.

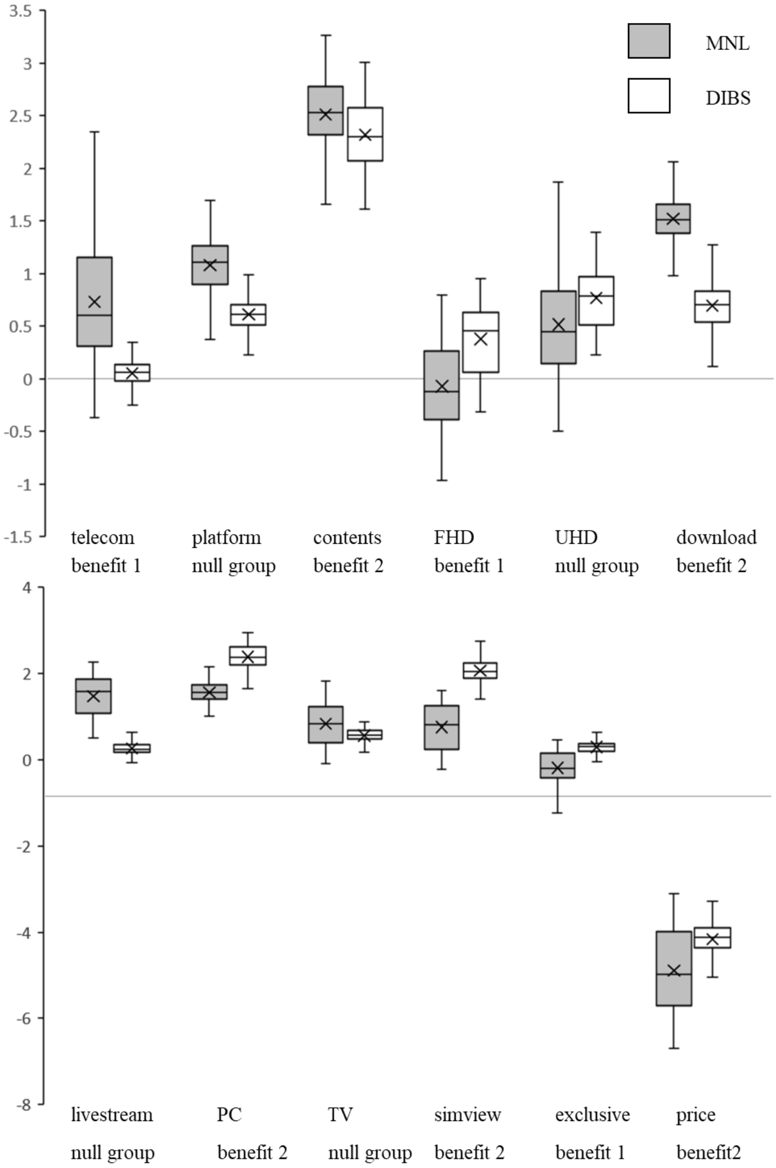

Figure 14. Comparison of $\bar{\beta}$ for MNL and DIBS model: OTT data

4.1.8 Conclusion and Implications

This study analyzed the consumer's preference for the OTT service market which is being rapidly adopted globally. Using the data acquired through DCE, which consists of eight main attributes of OTT service, consumers' preference for OTT service was analyzed by the basic models of multinomial logit (MNL) and benefit-based (BB) models. In addition, this study proposed benefit-scale (BS) model, indexed benefit-scale (IBS) model, and demographic indexed benefit-scale (DIBS) model and additional implications were derived.

Summary of Fit Statics on different models

Compared with the traditional model, MNL, the predictive fit of the SU model, which is a model in which the overall utility is satiated, was better, but the model fit that explains the in sample data was better in MNL. The model fit of the BB model was better than that of the MNL. The BS model with the scale parameter had better model fit than the traditional model and BB model. Scale heterogeneity in BS model between the classified benefit groups was 1.419 and 0.571, respectively. The IBS model, which is a model with an index based on the assignment probability estimated from BS, showed a slightly worse predictive fit than the MNL model or SU model. This is a different result than expected, but nevertheless, the in-sample hit rate of the IBS model was superior to that of the MNL model or BB model. In the IBS model, scale parameter was different from that of the BS model. As for the attribute to benefit assignment, the probabilistic models made a clear contribution to the improvement of the predictive fit of the model. From this result, the assumption that the assignment probabilities are heterogeneous seems to play an important role. Additionally, it was found that the predictive power and in-sample explanatory power of the DIBS model were improved when the demographic variable was included into the scale parameter as an intersection term in the IBS model.

Table 17. Summary of Fit Statistic: OTT Data

		In-sample		Holdout sample		s_k	
Models	LMD	Hit rate	Hit prob.	Hit rate	Hit prob.	s_1	s_2
MNL	-2020.432	0.790	0.762	0.530	0.528	-	-
SU	-2221.497	0.765	0.689	0.608	0.572	-	-
BB	-1816.836	0.834	0.768	0.582	0.564	1.000	1.000
IBS	-1823.109	0.822	0.756	0.535	0.523	0.995	1.005
DIBS	-1658.906	0.833	0.782	0.544	0.534	0.991	1.009
BS	-212.176	0.931	0.913	0.613	0.611	1.429	0.571

Attribute to Benefit Grouping

Estimated assignment probability indicates that the attributes of contents diversity (contents), price of monthly subscription (price), PC viewable (PC), simultaneous viewing (simview) are probabilistically grouped into one benefit group that satiates with each other. Attributes of telecommunication service providing OTT service (telecom), FHD image quality (FHD), and exclusive content (exclusive) are likely to be grouped as another benefit group.

Table 18. Attribute to benefit grouping: OTT data

Benefit group (k)	Attributes (n)	Remark
Null group	platform, UHD, livestream, TV	
Benefit 1	telecom, FHD, exclusive	Telecom related
Benefit 2	contents, download, PC, simview, price	IPTV related

Interpretation of Benefit Grouping

The author's interpretation of the benefit group is as follows. When consumers perceive OTT service in terms of benefit, the benefit group which attribute contents and price belong is composed of properties that can be compared with IPTV or cable TV service. Another benefit group is interpreted as attributes corresponding to telecommunication service providers, and the null group is interpreted as unique attributes that can be differentiated from other paid OTT service providers.

Scale parameter

Regarding satiation in BS model, benefit 2 was observed to be satiated easier than benefit 1. In other words, it was found that the satiation of properties similar to those of the traditional IPTV service was relatively fast, and the new properties of the other OTT service satiation relatively slowly.

The scale parameter was larger in the benefit 1 group (telecommunication service provider, FHD image quality and exclusive content provision).

Unique Attributes

The attributes that did not exhibit satiation were the type of platform operator, the quality of UHD or higher, real-time streaming content, and smart TV link option from BS model. They are the attributes that their (dis)utility does not satiate with other attribute (dis)utility. From estimated results of DIBS model, it women and younger individuals tend to value unique attributes more than men and elder individuals.

Implications for OTT service providers

To conclude, it would be reasonable to see that the OTT service not only competes with other OTT services, but also competes with traditional IPTV or cable TV.

When considering the situation of IPTV or cable TV SO providing OTT service, interpreting the OTT service as a service derived from the existing IPTV seems reasonable. From the perspective of service planners of OTT service providers based on services in the IPTV or cable TV SO business, it provides an implication that it is desirable to plan existing IPTV contents as a service that can be enjoyed on the go at an affordable price.

In addition, supporting UHD or higher image quality requires more servers to be built, which inevitably entails higher capital costs, so it must be approached carefully (Borocci et al., 2016). It is also necessary to be cautious about investing in increasing content diversity, because content diversity is an attribute that shows relatively high diminishing marginal utility property. Accordingly, if content diversity has been secured above a certain level, it may be more appropriate to provide exclusive content or live streaming option rather than diversification of contents. However, the cost for securing exclusive content should also be carefully taken into consideration.

4.2 The Study on Alternative Fuel Vehicle

4.2.1 Introduction

The introduction of electric vehicles and hydrogen vehicles, which are representative future transportation vehicles, are innovative products that differ in form from existing technologies, and the shape of the next-generation mobility market is expected to change depending on the degree of diffusion of the products.

Due to the advent of vehicles that use electricity and hydrogen as fuel, it is expected that change will take place from that of the traditional internal combustion engine vehicle era. In a situation where the transition to such an alternative fuel vehicle is obvious, a study is needed to approach the benefits in terms of how consumers perceive the attributes observed only in alternative fuel vehicles when compared with those of traditional fuel vehicles.

Among alternative fuel vehicles, Tesla is leading the global market, and it is coming out in the form of mid-size sedans and SUVs. There are no companies that are clearly leading the hydrogen car market yet, but Nikola is receiving great attention and is focusing on sales freight vehicles.

Hydrogen vehicles, which have emerged recently, convert stored hydrogen into electric energy and use it as a power source, and have advantages in terms of short charging time, long driving distance, and high fuel economy. The hydrogen electric vehicle market is currently in the initial stage of market formation, and the market is expected to steadily expand afterwards.

In this situation, alternative fuel vehicles have distinctly different properties than conventional fuel vehicles. In the case of electric and hydrogen vehicles, the ratio of charging station infrastructure, fuel economy, and maximum mileage are markedly different from those of conventional fossil fuel-based vehicles. In addition, electric vehicles have distinctly different properties as the time required to fully charge it takes several hours instead of minutes. It is important to understand how the interaction of these attributes affects consumers' preferences. In this situation, we want to understand which vehicles consumers prefer, observe which attributes are likely to be grouped into benefits, and understand how satiation takes place within benefits.

Shin et al. (2018) analyzed how next-generation automobiles affect consumers' vehicle choice and usage patterns using the Mixed Multiple Discrete-Continuous Extreme Value Model (MDCEV) using the statement preference data collected through DCE. Shin et al. (2019) also analyzed the consumer preference for next-generation vehicles by reflecting the recent attention of hydrogen cars as one of the attribute level in DCE. Fuel types, pollutant emission level, fuel mileage, charging infrastructure and vehicle price were used as attributes in DCE.

4.2.2 Data

The survey for this study was conducted through a 1:1 offline survey using purposive quota sampling method for Seoul and five metropolitan areas through a survey specialized agency, Gallup Korea Research Institute. 624 people aged 20 to 60 with driver's license were selected as respondents. The survey period was conducted for 3 weeks from July 18 to August 7, 2019, and the demographic characteristics of the sample including the allocation criteria are shown in Table 19.

Table 19. Demographic characteristics of respondents: Alternative Fuel Vehicle

Group		No. of Respondents	Component Ratio (%)
Total		624	100.0
Sex	Male	313	50.2
	Female	311	49.8
Age	20 to below 30	136	21.8
	30 to below 40	151	24.2
	40 to below 50	167	26.8
	50 to below 60	170	27.2
Region	Seoul	268	42.9
	Kyunggi Ilsan	17	2.7
	Kyunggi Bundang	14	2.2
	Incheon	81	13.0
	Busan	90	14.4
	Daegu	69	11.1
	Gwangju	42	6.7
	Daejeon	43	6.9
Education Level	High school graduates or lower	171	27.4
	College students or higher	453	72.6

Fuel Type

Fuel type attribute was composed of vehicle types that are currently available for purchase. Attribute levels were gasoline, diesel, LPG, electricity, and hydrogen were presented.

Charging Time

Charging time is an attribute specific to electric vehicles only, which means the average charging time required to charge the electric vehicle so that it can be used up to the maximum driving distance. Attribute level presented to respondents were 1 hour, 2 hours and 4 hours

Charging Insfrastructure

In the case of accessibility to charging stations, it is an attribute that applies to electric vehicles, LPG vehicles, and hydrogen vehicles. Relative accessibility to each type of charging station is compared in percentage rate to traditional gas stations.

Vehicle Type

In the case of a vehicle type, it is an attribute indicating the size of the vehicle to be purchased, and presented by dividing it into light/small/quasi-medium-sized vehicles, mid-sized vehicles, large vehicles, and SUV/RVs.

Fuel mileage

In the case of fuel cost, fuel cost required conversion in mileage units (oil: km/l, electricity: km/kWh, hydrogen: km/kg) between vehicle types. The fuel cost was presented in four levels: 500 won/10km, 1,000 won/10km, 1,500 won/10km, and 2,000 won/10km.

Price

Four levels of attribute level are proposed: 15 million won, 30 million won, 45 million won, and 60 million won.

Others

Car type refers to size of the car. Range is maximum driving range of vehicle when it is fully charged. Autonomous refers to the level of autonomous driving of the vehicle to be purchased.

Based on these attributes, the total number of attributes was set to eight, and it was assumed that all the attributes constituting the alternative fuel vehicle were the same.

Table 20. Discrete choice experiment's attribute, level and description: AFV

Attribute	Level	Description
Fuel type	Gasoline Diesel LPG Electric Hydrogen	Power source of vehicle
Charge time	1 hour 2 hours 4 hours	Charging time required to reach maximum driving distance when using an electric vehicle
Accessibility of gas/charge station	50% 70% 90%	The ratio of gas/charging stations available when the number of conventional gas stations is assumed to be 100%.
Car type	Small Midsize Large SUV/RV	The size of the vehicle
Mileage	500 won/10km 1,000 won/10km 1,500 won/10km 2,000 won/10km	Unit fuel cost required to drive 10km
Range	300km 450km 600km	Maximum driving distance after charging the vehicle to be purchased once
Level of autonomous driving	None Assistance Partial autonomous	Level of autonomous driving of the vehicle to be purchased. If there is no autonomous driving function, it is the same as the current vehicles.
Price	15 million won 30 million won 45 million won 60 million won	Purchase price of the vehicle you wish to purchase

This study composed a total of 32 alternatives through the orthogonal design mentioned above. In addition, 32 alternatives were categorized into 8 choice sets, 4 each and presented to respondents. As an example, one of the choice set in this study is presented in Table 21.

Table 21. Example of choice set: Alternative Fuel Vehicle

Attribute	Type A	Type B	Type C	Type D
Fuel type	LPG	Electric	Diesel	Hydrogen
Charge time	-	2 hours	-	-
Accessibility	50%	70%		50%
Car type	Small	SUV/RV	SUV/RV	SUV/RV
Mileage	1,000 won/10km	1,500 won/10km	500 won/10km	1,000 won/10km
Range(max)	450km	300km	450km	600km
Autonomous level	none	Partial autonomous	none	Assistance
Price	15 million won	45 million won	45 million won	30 million won
Choice	Type A	Type B	Type C	Type D

4.2.3 MNL & Benefit-based Model: Estimation Results

In estimating fit statistics for alternative fuel vehicles in Table 22, after 20,000 iterations of Marcov Chain Monte Carlos (MCMC) were run for each K, only the 10th data among the last 10,000 data were extracted and used. It can be seen that the benefit-based discrete selection model of K=1 or more is more appropriate than the standard logit model (K=0). Depending on the criteria, best suited model could be K=3 (highest LMD and in-sample statistic) or K=1 (Holdout sample statistic). I used K=2 as a baseline benefit-based model to provide comparison result with further benefit-scale model.

Table 22. Fit Statistics (MNL & Benefit-based Model): Alternative Fuel Vehicle data

		In-sample		Holdout sample	
Models	LMD	Hit rate	Hit prob.	Hit rate	Hit prob.
Multinomial Logit Model (K=0)	-2612.989	0.691	0.659	0.449	0.434
Benefit-based Model (K=1)	-2293.482	0.774	0.696	0.467	0.438
Benefit-based Model (K=2)	-2233.475	0.779	0.700	0.462	0.432
Benefit-based Model (K=3)	-2232.580	0.790	0.715	0.461	0.435

The assignment probability for each benefit K is shown in Table 20. It shows that the benefit-based discrete selection model, which follows the law of diminishing marginal utility, is more suitable as all attributes except range in K=1 are assigned as benefit 1. At K=3, the assignment probability was 1/(K+1), indicating that it was not specific to a specific benefit.

Table 23. Posterior Estimates of Assignment Probabilities: Alternative Fuel Vehicle data

	K=1		K=2			K=3			
Attributes	Null	Benefit1	Null	Benefit1	Benefit2	Null	Benefit1	Benefit2	Benefit3
diesel	0.50	**0.50**	0.19	0.39	0.42	0.22	0.24	0.26	0.28
LPG	0.49	**0.51**	0.37	0.30	0.32	0.29	0.24	0.25	0.23
electric	0.17	**0.83**	0.16	0.39	0.45	0.12	0.24	0.23	0.41
hydrogen	0.22	**0.78**	0.19	0.43	0.39	0.22	0.25	0.26	0.27
charge	0.15	**0.85**	0.27	0.40	0.32	0.28	0.25	0.23	0.24
access	0.48	**0.52**	0.18	0.47	0.36	0.24	0.25	0.26	0.26
midsize	0.29	**0.71**	0.25	0.40	0.36	0.21	0.26	0.24	0.29
large	0.07	**0.93**	0.24	0.41	0.36	0.20	0.24	0.25	0.30
SUV	0.15	**0.85**	0.19	0.41	0.41	0.16	0.27	0.28	0.30
fuel	0.39	**0.61**	0.23	0.33	0.43	0.14	0.24	0.24	0.38
range	**0.77**	0.23	0.48	0.28	0.25	0.27	0.25	0.25	0.23
assistance	0.29	**0.71**	0.23	0.40	0.37	0.20	0.27	0.24	0.29
autonomous	0.41	**0.59**	0.24	0.42	0.35	0.17	0.29	0.27	0.28
price	0.13	**0.87**	0.09	0.45	0.46	0.11	0.23	0.25	0.41

Table 24. and Figure. 16., parameter estimates of standard multinomial logit model (K=0) and benefit-based model for K=2 are compared. The signs of the estimates for each model were not significantly different.

Table 24. Posterior estimates of the $\bar{\beta}$ (MNL & BB): Alternative Fuel Vehicle Data

Variables	MNL (K=0)	K=1	K=2	K=3
diesel	-0.875	-0.775	-1.035	-0.62
	(0.183)	(0.480)	(0.326)	(0.354)
LPG	-1.128	-1.354	-0.438	-0.311
	(0.273)	(0.195)	(0.359)	(0.329)
electric	1.169	1.644	2.115	2.855
	(0.266)	(0.340)	(0.486)	(0.359)
hydrogen	-0.64	-0.547	0.224	0.258
	(0.236)	(0.336)	(0.368)	(0.372)
charge	-0.649	-0.829	-0.693	-0.882
	(0.080)	(0.100)	(0.095)	(0.076)
access	1.034	1.779	2.158	3.047
	(0.367)	(0.278)	(0.548)	(0.382)
midsize	0.708	1.555	1.467	1.869
	(0.118)	(0.227)	(0.302)	(0.283)
large	0.505	1.101	0.894	1.567
	(0.244)	(0.359)	(0.405)	(0.352)
SUV	1.045	1.866	1.564	2.273
	(0.152)	(0.298)	(0.342)	(0.340)
fuel	-0.826	-1.330	-1.306	-1.429
	(0.113)	(0.148)	(0.149)	(0.190)
range	0.172	0.173	0.208	0.29
	(0.050)	(0.079)	(0.070)	(0.083)
assistance	0.005	0.111	-0.287	-0.369
	(0.096)	(0.204)	(0.206)	(0.176)
autonomous	-0.153	0.074	-0.256	-0.470
	(0.105)	(0.106)	(0.198)	(0.283)
price	-0.813	-0.976	-0.997	-1.140
	(0.062)	(0.083)	(0.090)	(0.099)

Notes: Standard deviation in parenthesis.

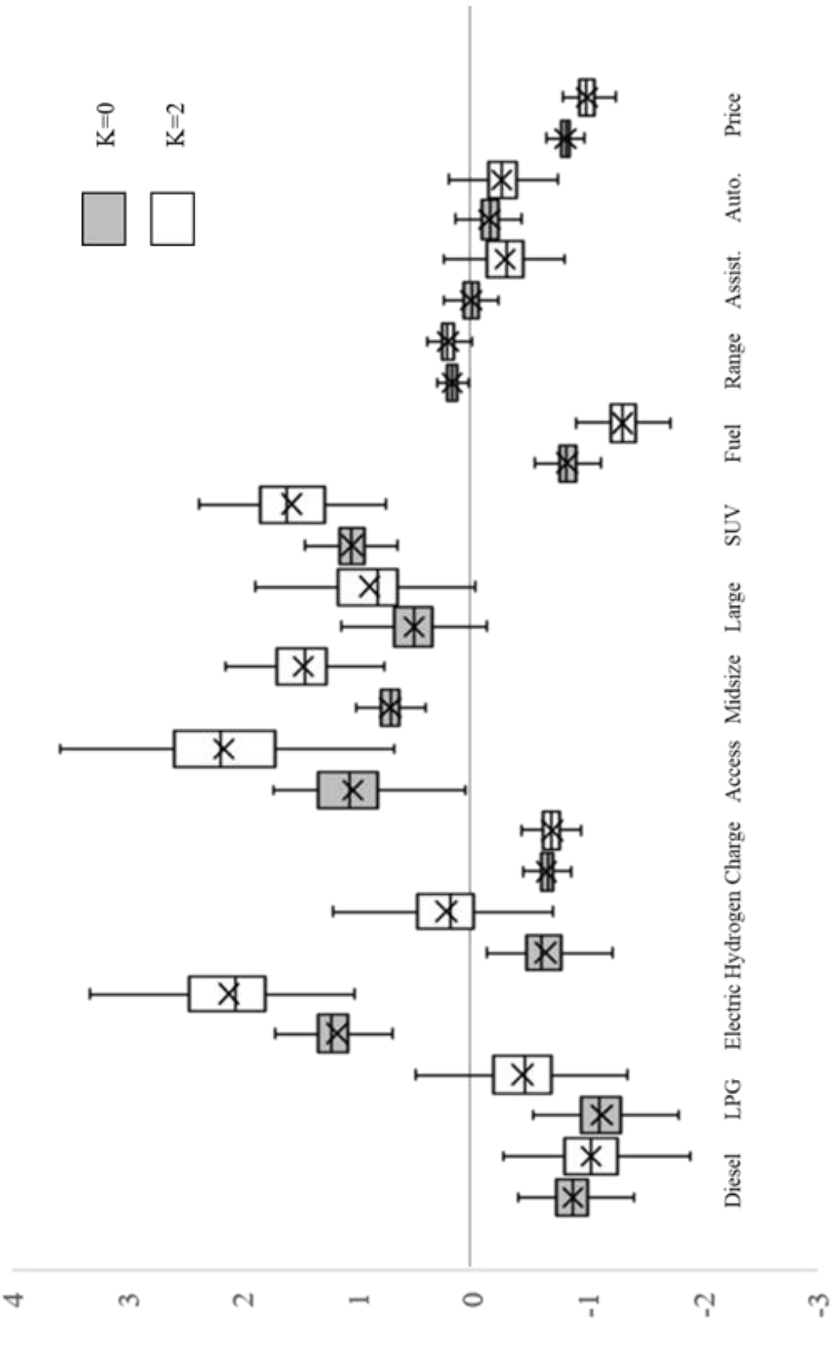

Figure 15. Comparison of $\bar{\beta}$ for MNL and BB model: Alternative Fuel Vehicle Data

4.2.4 Satiation in Utility Model: Estimation Results

Model fit statistic of satiation in utility (SU) model is compared with standard multinomial logit (MNL), benefit-based (BB) model in Table 25. SU model showed best predictive fit for holdout sample hit rate only. Therefore, I suggest careful approach on using SA model from Table 25. Even though SU model have shown good predictive fit, further empirical verification for discrete choice experiment with fewer attributes is required.

Table 25. Fit Statistics (MNL, Benefit-based & Satiation in utility model): AFV Data

		In-sample		Holdout sample	
Models	LMD	Hit rate	Hit prob.	Hit rate	Hit prob.
Multinomial Logit Model	-2542.647	0.691	0.659	0.449	0.434
Benefit-based Model	-2247.972	0.772	0.691	0.461	0.431
Satiation in utility Model	-2640.775	0.704	0.628	0.466	0.426

Parameter estimates of standard multinomial logit model (MNL) and SA model are compared in Table 26. and Figure 17. The signs of the estimates for each model were not significantly different.

Table 26. Posterior estimates of the $\bar{\beta}$ (MNL & SU): Alternative Fuel Vehicle Data

Variables	Multinomial Logit (MNL)	Satiation in utility (SU)
diesel	-0.875	-1.788
	(0.183)	(0.369)
LPG	-1.128	-1.352
	(0.273)	(0.270)
electric	1.169	1.941
	(0.266)	(0.345)
hydrogen	-0.64	0.477
	(0.236)	(0.386)
charge	-0.649	-0.729
	(0.080)	(0.107)
access	1.034	2.051
	(0.367)	(0.385)
midsize	0.708	0.362
	(0.118)	(0.309)
large	0.505	-0.326
	(0.244)	(0.445)
SUV	1.045	0.635
	(0.152)	(0.481)
fuel	-0.826	-0.938
	(0.113)	(0.177)
range	0.172	-0.019
	(0.050)	(0.048)
assistance	0.005	0.949
	(0.096)	(0.335)
autonomous	-0.153	-0.011
	(0.105)	(0.271)
price	-0.813	-0.973
	(0.062)	(0.062)

Notes: Standard deviation in parenthesis.

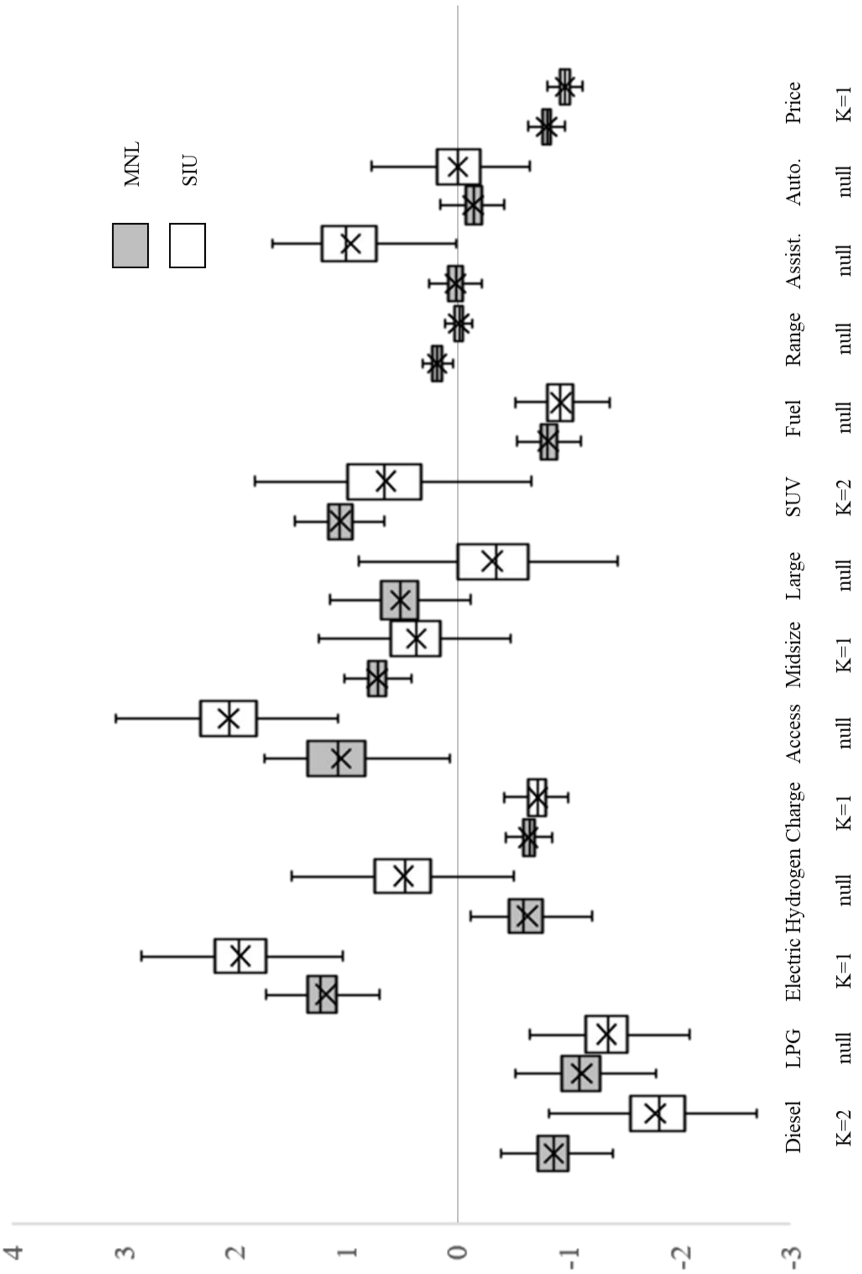

Figure 16. Comparison of $\bar{\beta}$ for MNL and SU model: Alternative Fuel Vehicle Data

4.2.5 Benefit-scale Model: Estimation Results

The actual number of benefit groups, K, was assumed to be 2. Table 22 presents comparison of the value of initial 20,000 MCMC iterations in the multinomial logit model, benefit-based model and proposed benefit-scale model. It can be seen that proposed benefit-scale model achieved better model fit statistics.

Table 27. Fit Statistics (MNL, BB & BS): Alternative Fuel Vehicle Data with s_k, K=2

		In-sample		Holdout sample	
Models	LMD	Hit rate	Hit prob.	Hit rate	Hit prob.
Multinomial Logit Model	-2542.647	0.691	0.659	0.449	0.434
Benefit-based Model	-2247.972	0.772	0.691	0.461	0.431
Benefit-scale Model	-1112.967	0.904	0.872	0.477	0.470

Table 28. shows the estimated assignment probability (θ_{nk}) and the scale parameter (s_k) of each benefit group. Numbers in bold indicates a probability of 0.5 or more.

Table 28. Posterior Estimates of Assignment Probability: Alternative Fuel Vehicle Data

	Benefit-based Model (K=2)			Benefit-scale Model (K=2)		
Attributes	Null	Benefit1	Benefit2	Null	Benefit1	Benefit2
diesel	0.19	0.39	0.42	0.15	0.35	**0.50**
LPG	0.37	0.30	0.32	0.26	0.31	0.42
electric	0.16	0.39	0.45	0.11	**0.73**	0.16
hydrogen	0.19	0.43	0.39	0.18	0.47	0.35
charge	0.27	0.40	0.32	0.20	**0.51**	0.29
access	0.18	0.47	0.36	0.23	0.40	0.37
midsize	0.25	0.40	0.36	0.09	**0.56**	0.34
large	0.24	0.41	0.36	0.23	0.48	0.29
SUV	0.19	0.41	0.41	0.28	0.20	**0.53**
fuel	0.23	0.33	0.43	0.25	0.41	0.34
range	0.48	0.28	0.25	0.23	0.48	0.29
assistance	0.23	0.40	0.37	0.09	0.46	0.44
autonomous	0.24	0.42	0.35	0.26	0.46	0.28
price	0.09	0.45	0.46	0.09	**0.62**	0.30
s_k		1.000	1.000		1.061	0.939

As shown in Table 28, with the introduction of the scale parameter, the convergence of the attribute to benefit grouping became clearer. For the attributes hydrogen, large, range, assistance and autonomous, the assignment probability for benefit group 2 is 0.45 to 0.50, and it is difficult to be considered to belong to a null group. The researcher expects to be able to interpret each benefit group as follows.

Table 29. Attribute to benefit grouping: Alternative Fuel Vehicle data

Benefit group (k)	Attributes (n)	Remark
Null group	LPG, *hydrogen*, access, *large*, fuel, *range*, *assistance*, *autonomous*	-
Benefit 1	electric, charge, midsize, price	Electric
Benefit 2	diesel, SUV	SUV

Assignment Probability

The main result is that the electric vehicle attribute, electric vehicle charging time, mid-size vehicle attribute, and price are included in same benefit as benefit 1. In addition, satiation between the diesel vehicle attribute and SUV/RV attribute included in benefit 2 is also observed.

Null Attributes

Attributes grouped in null group has important implication for AFV designers. LPG and hydrogen as a fuel type is likely to provide unique utility to consumers. Charging infrastructure(access) attribute was also identified as unique attribute. Other attributes included large size car(large), fuel mileage(fuel), maximum driving range(range), autonomous driving options(assistance, autonomous).

Interpretation of attribute to benefit grouping

The grouping of Benefit 1 provides the following interpretation. By simply interpreting the result that price and the electric vehicle charging time are included in the same benefit, we can say that the disutility from high price is mutually satiated with the disutility from long charging time. This means the disutility from long charging time is satiated when the price is high and disutility from charging time feels relatively small to price. This satiation in disutility may not be intuitive. However, this can be interpreted by comparing the disutility of a vehicle with a long charging time and a vehicle with a short charging time when the electric vehicle is inexpensive. If the charging time is lengthy, the low price of the electric vehicle has a relatively small effect on the selection. Conversely, if the electric vehicle price is high, even if the charging time is short, it does not significantly affect the selection.

In addition, the utility of electric vehicles is likely to be mutually satiated with the utility of medium-sized vehicles. On the other hand, when the utility of an electric vehicle is a large vehicle or an SUV/RV vehicle, such satiation is not likely to occur. From this finding, it could be an excellent strategy for electric car manufacturers to provide SUV/RV vehicles rather than planning large cars.

If you interpret Benefit 2, the utility for SUV is satiated in case of diesel vehicles. When an SUV/RV vehicle is an alternative fuel vehicle such as an electric vehicle, the utility of the SUV/RV itself is not satiated.

Parameter estimates

In Table 30, the positive and negative sign directions of the base benefit based model and the with scale parameter model are same except for hydrogen attribute.

Table 30. Posterior estimates $\bar{\beta}$ (MNL & BS): Alternative Fuel Vehicle Data

Variables	Multinomial Logit Model	Benefit-scale Model
diesel	-0.875	0.019
	(0.183)	(0.777)
LPG	-1.128	-1.493
	(0.273)	(0.738)
electric	1.169	5.619
	(0.266)	(0.770)
hydrogen	-0.64	0.417
	(0.236)	(0.894)
charge	-0.649	-2.527
	(0.080)	(0.265)
access	1.034	3.192
	(0.367)	(0.936)
midsize	0.708	3.574
	(0.118)	(0.718)
large	0.505	2.943
	(0.244)	(0.998)
SUV	1.045	3.837
	(0.152)	(0.651)
fuel	-0.826	-2.951
	(0.113)	(0.319)
range	0.172	0.171
	(0.050)	(0.242)
assistance	0.005	0.833
	(0.096)	(0.431)
autonomous	-0.153	-1.842
	(0.105)	(0.426)
price	-0.813	-2.426
	(0.062)	(0.284)

Notes: Standard deviation in parenthesis.

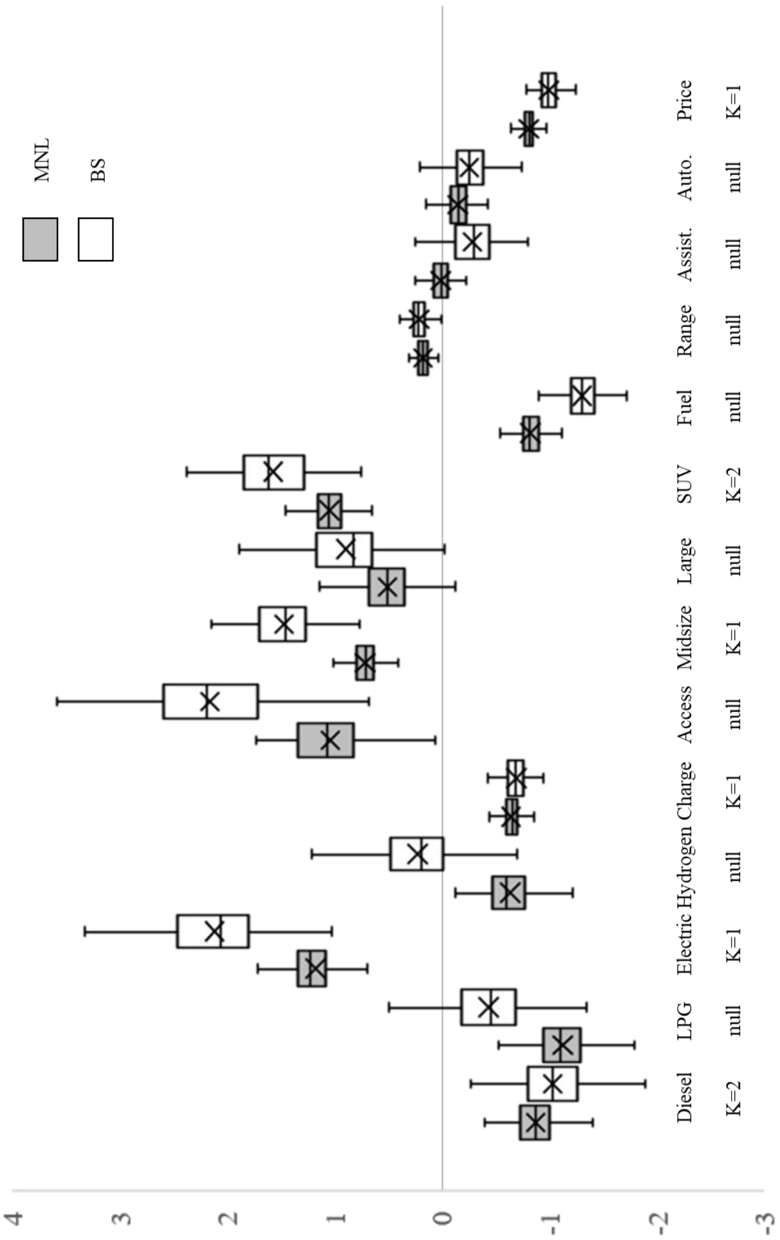

Figure 17. Comparison of $\bar{\beta}$ for MNL and BS: Alternative Fuel Vehicle Data

Implications

It is worth noting that the disutility of price and charging time satiates with each other, but interpretation must be taken with caution. A typical misinterpretation is that in the case of an electric vehicle with a very high price and a very long charging time, there is no need to significantly improve the charging time because these two disutilities satiate with each other. Proper interpretation is to interpret that finding the right balance of attribute levels brings relatively little disutility to consumers[8].

[8] For further understanding, refer to the satiation within benefit graph presented in Figure 6. .

4.2.6 Indexed Benefit-scale Model: Estimation Results

Model specification is identical to Eq. (3.20), which is benefit-scale model using assumed $\{\tau_{nk}\}$ based on criteria introduced in Section 3.4.1. As can be seen in Table 31, IBS model provided lower fit statistics.

Table 31. Fit Statistics (MNL, Benefit-based & Indexed Benefit-scale model): AFV Data

		In-sample		Holdout sample	
Models	LMD	Hit rate	Hit prob.	Hit rate	Hit prob.
Multinomial Logit Model	-2542.647	0.691	0.659	0.449	0.434
Benefit-based model	-2247.972	0.772	0.691	0.461	0.431
Indexed Benefit-scale Model	-2781.477	0.696	0.609	0.436	0.427

Parameter Estimates

Signs of estimated parameter $\bar{\beta}$ were significantly equal to multinomial logit but the variance of parameter estimates were higher for attributes that belong to benefit 1 as benefit 1's scale parameter is estimated to be 0.337.

Table 32. Posterior estimates $\bar{\beta}$: Alternative Fuel Vehicle Data with scale parameter

Variables	Multinomial logit Model	Indexed Benefit-scale Model
diesel	-0.875	-0.813
	(0.183)	(0.130)
LPG	-1.128	-1.076
	(0.273)	(0.165)
electric	1.169	-1.03
	(0.266)	(0.344)
hydrogen	-0.64	-0.601
	(0.236)	(0.146)
charge	-0.649	-1.713
	(0.080)	(0.191)
access	1.034	0.778
	(0.367)	(0.288)
midsize	0.708	3.087
	(0.118)	(0.342)
large	0.505	-0.246
	(0.244)	(0.115)
SUV	1.045	0.232
	(0.152)	(0.084)
fuel	-0.826	-0.824
	(0.113)	(0.112)
range	0.172	0.135
	(0.050)	(0.039)
assistance	0.005	0.011
	(0.096)	(0.082)
autonomous	-0.153	-0.103
	(0.105)	(0.101)
price	-0.813	-1.792
	(0.062)	(0.191)

Notes: Standard deviation in parenthesis.

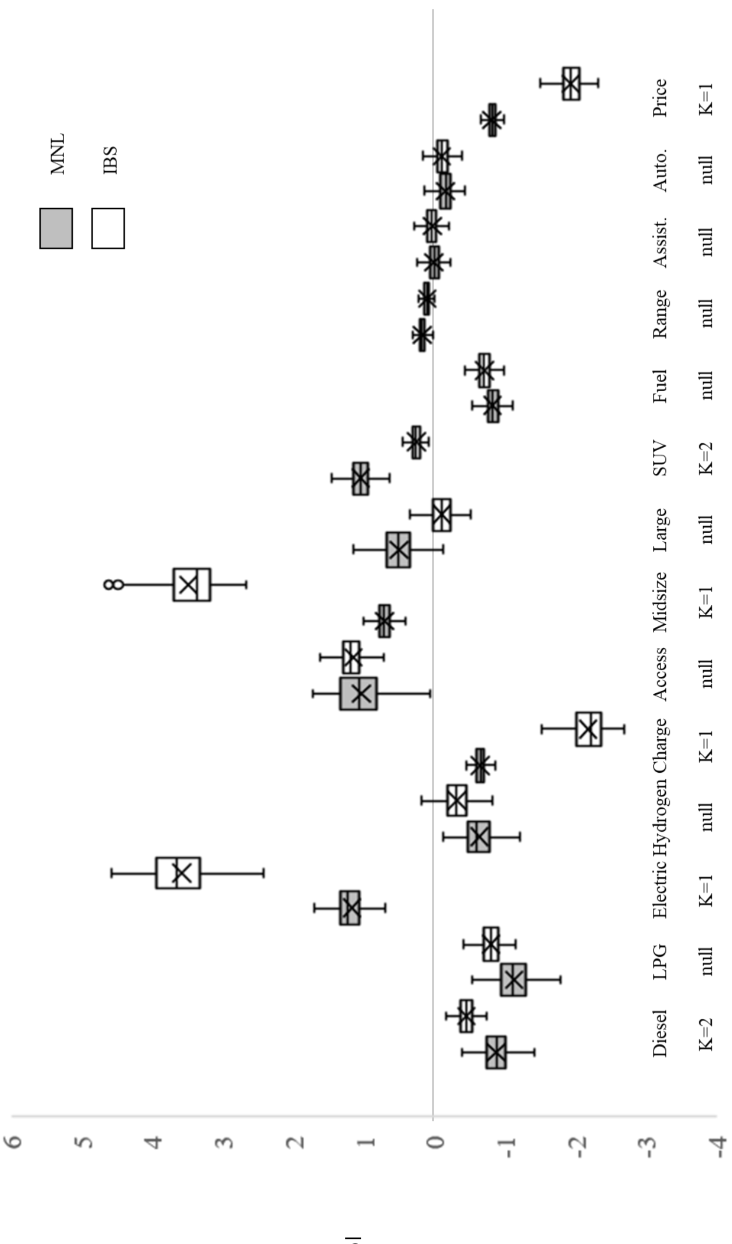

Figure 18. Comparison of $\bar{\beta}$ for MNL and IBS: OTT data

4.2.7 Demographic Indexed Benefit-scale Model: Results

Demographic variables used is sex and age (10 years). Introducing demographic variable in scale parameter increased model fit statistics as shown in Table 33. However, as mentioned in OTT service data, a careful approach is needed to generalize the use of demographic variables.

Table 33. Fit Statistics (IBS & DIBS model): Alternative Fuel Vehicle Data

		In-sample		Holdout sample	
Models	LMD	Hit rate	Hit prob.	Hit rate	Hit prob.
Indexed Benefit-scale Model	-2781.477	0.696	0.609	0.436	0.427
DIBS Model	-2533.427	0.710	0.630	0.433	0.414

Demographic Variables

Study used sex and age as demographic variable to investigate heterogeneity in scale parameter. From estimated result, γ_{male} and γ_{age} were 0.304 and 0.144 respectively. Which indicates that women and younger individuals consider the unique attribute more important. However, a careful approach is needed to generalize and introduce these variables as degree of freedom increases in the model as variables are added.

Table 34. Posterior estimates of the $\bar{\beta}$ (MNL & DIBS): Alternative Fuel Vehicle Data

Variables	Multinomial Logit (MNL)	DIBS
diesel	-0.875	-0.505
	(0.183)	(0.088)
LPG	-1.128	-0.878
	(0.273)	(0.153)
electric	1.169	1.615
	(0.266)	(0.758)
hydrogen	-0.64	-0.358
	(0.236)	(0.142)
charge	-0.649	-1.776
	(0.080)	(0.186)
access	1.034	1.203
	(0.367)	(0.196)
midsize	0.708	2.298
	(0.118)	(0.467)
large	0.505	-0.073
	(0.244)	(0.139)
SUV	1.045	0.284
	(0.152)	(0.097)
fuel	-0.826	-0.777
	(0.113)	(0.101)
range	0.172	0.130
	(0.050)	(0.048)
assistance	0.005	-0.021
	(0.096)	(0.085)
autonomous	-0.153	-0.129
	(0.105)	(0.097)
price	-0.813	-2.086
	(0.062)	(0.159)

Notes: Standard deviation in parenthesis.

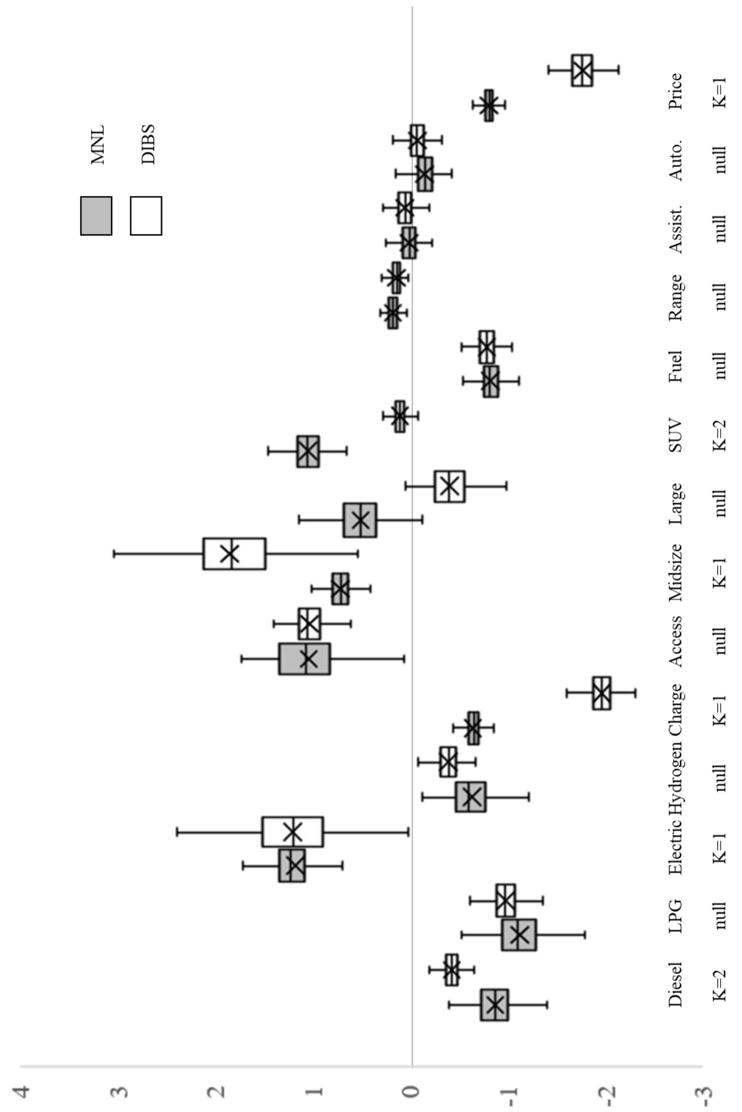

Figure 19. Comparison of $\bar{\beta}$ for MNL and DIBS model: Alternative Fuel Vehicle Data

4.2.8 Conclusion and Implications

Summary of Fit Statics on different models

Compared with the traditional model, MNL, the SU model that the overall utility is satiate improved hit rate in the holdout sample, but other overall model fits were worse. The benefit-based model had better model fit than MNL. The BS model had better model fit than the traditional model and the BB model, and the scale heterogeneity between benefit groups was estimated to be 0.961 and 1.039. The attribute-to-benefits assignment in BS model clearly contributes to the improvement of the predictive fit of the model. This fact seems to be an evidence that the method of grouping attribute to benefit for each individual is indeed heterogeneous. IBS model showed worse fit statistic than the MNL model. Additionally, the DIBS model, which included demographic variables into the IBS model as a cross term in the scale parameter, did not have a better predictive fit than the IBS model, but showed minor improvements in the dimension of the in-sample fit.

Table 35. Summary of Fit Statistic: Alternative Fuel Vehicle Data

		In-sample		Holdout sample		s_k	
Models	LMD	Hit rate	Hit prob.	Hit rate	Hit prob.	s_1	s_2
MNL	-2542.647	0.691	0.659	0.449	0.434	-	-
SU	-2640.775	0.704	0.628	0.466	0.426	-	-
BB	-2247.972	0.772	0.691	0.461	0.431	1.000	1.000
IBS	-2781.477	0.696	0.609	0.436	0.427	0.337	1.663
DIBS	-2533.427	0.710	0.630	0.433	0.414	0.326	1.674
BS	-1112.967	0.904	0.872	0.477	0.470	0.961	1.039

Attribute to Benefit Grouping

Analyzing the assignment probability in the benefit-scale model shows that electric vehicles, electric vehicle charging time, medium size, and price attributes are grouped into one benefit group. Attributes diesel and SUV/RV are also likely to be grouped into another benefit group.

Table 36. Attribute to benefit grouping: Alternative Fuel Vehicle data

Benefit group (k)	Attributes (n)	Remark
Null group	LPG, hydrogen, access, large, fuel, range, assistance, autonomous	-
Benefit 1	electric, charge, midsize, price	Electric
Benefit 2	diesel, SUV	SUV

Interpretation of Benefit Grouping

The grouping of benefit 1 and 2 provides implications for electric vehicle manufacturers. The utility of electric vehicles is not satiated when it is large size vehicle or SUV/RV vehicles rather than midsize cars. Launching electric SUV, such as Tesla model X, can provide higher utility to consumers as a different type of SUV.

Scale parameter

Satiation heterogeneity in benefit-scale model was not clearly found but it was clear in indexed model. This can be due to the fact that there were many attributes that attribute to benefit grouping were not clear.

Unique Attributes

The attributes that did not exhibit satiation were LPG, hydrogen, access, large, fuel, range, assistance, autonomous from BS model. Also, it could be concluded that women and younger individuals tend to value unique attributes more than men and elder individuals from estimated results of DIBS model.

Estimated Results

Summarizing parameter estimation results, consumers preferred electric vehicles the most as fuel type. Hydrogen vehicles had similar preference level as traditional fuel vehicles (gasoline, diesel). LPG vehicle was analyzed to be the least preferred. In addition, it was found that the charging time is very important attribute for electric vehicles and the maximum driving range was not so important.

Implications for Electric vehicle manufacturers

Electric vehicle manufacturers planners should plan performance by considering technical performance related to battery charging time with vehicle price together. Particularly, when it is difficult for electric vehicle manufacturers to shorten the charging time due to technical (or economical) reasons, it would be a superior strategy to improve attributes that belong to Null group or Benefit 2. This include launching SUV/RV vehicles, launching large-size vehicles, improving fuel economy, improving maximum driving distance, and providing driving assistance option. However, since the magnitude of the additional utility provided by the maximum mileage improvement and driving assistance function is small in magnitude, other strategies such as launching large-sized vehicles, SUV/RV vehicles, and efforts to improve fuel efficiency will be more realistic strategy.

Chapter 5. Summary and Conclusion

5.1 Concluding Remarks and Contributions

The proposed benefit-scale model showed superior performance in data explanatory power, predictive power, and assignment probability convergence than the standard multinomial logit and benefit-based model, and provided different interpretations. In particular, the major contribution of this model is that the convergence of the assignment probability is greatly improved. This is because the main contribution of the existing benefit-based model is to look at the probabilistic grouping between the attribute and the benefit without giving any prior relationship between the attribute and the benefit[9].

Another key advantage of benefit-scale approach is that it permits us to make use of DCE data with sparse information more effectively. This dissertation have shown how to extract and implement decision importance information using benefit-scale model based on Bayesian learning method based on Monte-Carlo Marcov Chain simulation.

Also further application of benefit-scale approach such as indexing and use of demographic data on scale parameter is discussed. I find that overall these applications produce qualitatively similar results with standard multinomial logit or benefit-based model, and does so without our having to understand benefit formation structure.

[9] In addition to that, the benefit scale model inherits the advantages of the existing benefit−based model. Which means no additional questionnaires are required, and the relationship between attributes and benefits does not need to be hypothesized in advance.

5.2 Limitations and Future Studies

Among the three rules constituting DCE, the valuation rule, the integration rule, and the choice rule, the benefit-based model is a rule mainly applied to the integration rule. Accordingly, benefit scale model can be flexibly applied to incorporate other behavioral economic models that corresponds to valuation rule and choice rule. For example, reference dependent model, uncertainty model, time discounting model that corresponds to valuation rule and attribute non-attendance model, random regret minimization model which corresponds to choice rule. These applications are left as a future study.

Although benefit-scale approach is practical for predictive purpose with small number of choice task data, more efficient and practical procedures for comparing different benefit is still needed. One might reject benefit-scale approach for interpretative reason, but benefit-scale approach still provides a way to maximize the fit for discrete choice experiment data.

Future work should investigate more fully the properties of benefit-scale model, alternative estimation method and identification schemes. In particular, further comparison of estimation methods based Bayesian learning methods seems worthwhile.

Another interesting direction is to try to capture the heterogeneity of the scale parameter in the benefit-scale model, the applicability of the scale parameter was tested in this study through the DIBS model, but it is left as future study to understand the heterogeneity of the scale parameter in the BS model itself.

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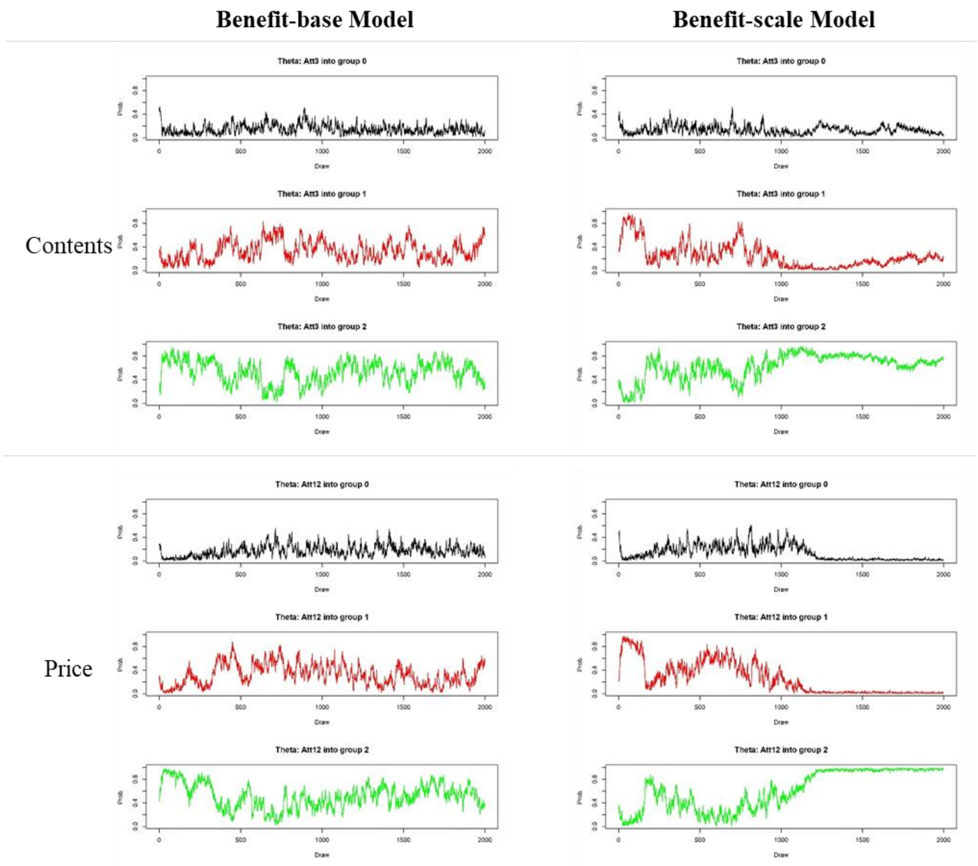
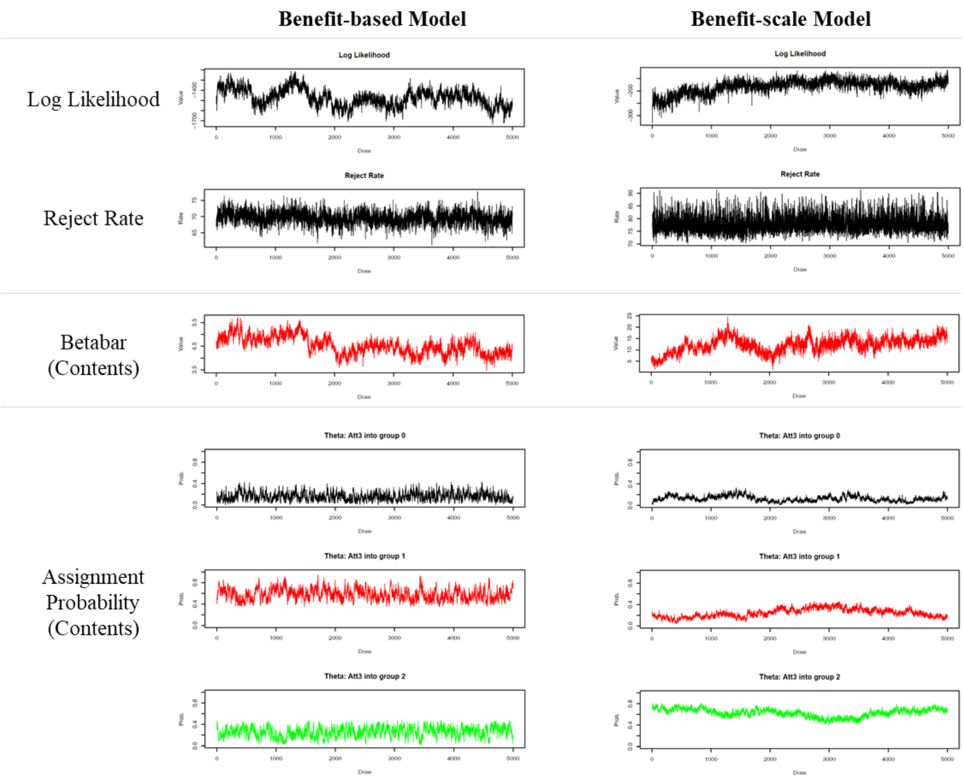
Appendix 1: Improvement in convergence of assignment probability

From trace plot of assignment probability in benefit-based model and benefit-scale model for initial 20,000 iterations, we can see attribute contents and price possess very high correlation within benefit group. We can see that benefit-scale model shows better performance in convergence of assignment probabilities after 12,000 iterations.



Appendix 2: Discussion on existence of local solutions

Both Benefit-based model and Benefit-scale model both exhibited convergence in model-fit statistics. I provide trace-plots of benefit-based model and benefit-scale model for comparison.



Appendix 3: Discussion on sensitivity of scale parameter's prior

Setting the different prior η_k of Dirichlet distribution resulted in model fit loss (baseline is 3). I present estimation results of three different value of prior η_k =0, 3, 10.

Table 37. Sensitivity of model fit when scale parameter prior, η_k differs

	In-sample		Holdout sample		s_k	
Models	Hit rate	Hit prob.	Hit rate	Hit prob.	s_1	s_2
$\eta_k = 0$	0.865	0.857	0.572	0.571	1.531	0.469
$\eta_k = 3$	0.931	0.913	0.613	0.611	1.429	0.571
$\eta_k = 10$	0.852	0.802	0.552	0.542	1.169	0.831

Also, assignment probability was different from η_k =3 when η_k = 0, but resulted in very similar assignment probability when η_k =10.

Table 38. Sensitivity of assignment probability when scale parameter prior, η_k differs

	$\eta_k = 0$			$\eta_k = 3$			$\eta_k = 10$		
Attributes	Null	Benefit1	Benefit2	Null	Benefit1	Benefit2	Null	Benefit1	Benefit2
telecom	**0.54**	0.30	0.16	0.24	**0.63**	0.13	**0.37**	0.27	0.35
platform	0.36	**0.42**	0.23	**0.57**	0.23	0.20	**0.47**	0.25	0.28
contents	0.14	0.19	**0.68**	0.12	0.12	**0.76**	0.15	0.25	**0.60**
FHD	0.09	0.41	**0.50**	0.15	**0.57**	0.28	0.24	**0.50**	0.26
UHD	**0.38**	0.38	0.24	0.35	0.18	**0.46**	0.25	0.24	**0.52**
download	0.14	**0.46**	0.40	0.26	0.09	**0.65**	0.22	0.29	**0.49**
livestream	0.28	0.36	**0.36**	**0.64**	0.12	0.24	**0.36**	0.31	0.34
PC	0.05	0.06	**0.89**	0.19	0.24	**0.58**	0.19	0.34	**0.47**

TV	**0.51**	0.30	0.19	0.32	0.18	**0.49**	0.29	0.25	**0.46**
simview	0.25	0.22	**0.53**	0.09	0.12	**0.79**	0.16	0.27	**0.57**
exclusive	0.37	**0.46**	0.17	0.37	**0.51**	0.12	0.35	**0.40**	0.24
price	0.02	0.01	**0.97**	0.07	0.04	**0.90**	0.17	0.25	**0.58**
s_k		1.531	0.469		1.429	0.571		1.169	0.831

The fact that satiation parameter is sensitive to the prior setting could be criticized as a weakness of this model that, but I would like to emphasize that the model's fit was best at η_k =3, the prior used in the benefit-based model is also 3, and it is also common in the field of Bayesian learning that different prior setting often produces different results. Therefore, setting prior η_k as 3 can be justified.

Appendix 4: Discrete Choice Experiment questionnaire: OTT service

유료 OTT 서비스 유형별 선호도 질문 안내문

1. 지금부터는 가상의 유료 OTT 서비스에 대한 유형별 선호도를 묻는 질문입니다.
2. 귀하께서 응답하실 유형별 선호도 질문 구성은 다음과 같습니다.
   1) 유료 OTT 서비스 설명문 (유료 OTT 서비스의 여러 속성과 속성별 수준에 대한 설명)
   2) 유료 OTT 서비스 선호 순위 질문 8개 (설명문에서 제시한 8개의 속성 수준을 조합하여 구성한 가상의 유료방송서비스 제시)
3. 귀하께서는 우선, 다음 설명문을 숙지해 주십시오.

▣ 유료 OTT 서비스 설명문

속성		속성 설명 및 수준
1. 서비스 제공자	설명	**통신사업자**는 기존 IPTV의 실시간 채널과 VOD 서비스를 동일하게 OTT 서비스에서 제공 (예: SKT 옥수수, KT올레TV모바일, LG U+ TV) **방송사업자**는 지상파/종편/케이블TV 사업자가 독자적으로 OTT 서비스를 개발하여 자사 콘텐츠 제공 (예: POOQ, TVING) **플랫폼 사업자**는 동영상 플랫폼 사업자가 인터넷을 통해 독자적인 서비스 제공 (예: 넷플릭스, 왓차플레이, 네이버TV, 카카오TV 등)
	수준 (3개)	① 통신사업자 ② 방송사업자 ③ 플랫폼사업자
2. 콘텐츠 다양성	설명	일반적으로 유료방송서비스(IPTV, 케이블TV) 등에서 제공하는 콘텐츠 수를 기준으로 한 개의 유료 OTT 서비스에서 제공하는 콘텐츠의 다양성
	수준 (3개)	① 100% (유료방송서비스 콘텐츠 수 대비 100% 수준) ② 70% (유료방송서비스 콘텐츠 수 대비 70% 수준) ③ 40% (유료방송서비스 콘텐츠 수 대비 40% 수준)
3. 최대 화질	설명	화면의 선명도 및 해상도 수준으로 UHD 화질과 Full HD 화질은 각각 HD 화질의 8배와 2배임
	수준 (3개)	① HD 화질 ② Full HD 화질 (HD 화질의 2배) ③ UHD 화질 이상 (HD 화질의 8배)
4. 시청 가능 형태	설명	원하는 방송 프로그램이나 콘텐츠를 시청할 수 있는 방법 - **VOD 스트리밍**은 해당 콘텐츠를 스트리밍으로 다시 볼 수 있는 기능 - **다운로드 기능**은 인터넷을 통해 콘텐츠를 다운로드하여 추후에 데이터 소비 없이 시청 가능함 - **라이브 스트리밍**은 실시간 방송을 인터넷 또는 데이터 소비를 통해 시청할 수 있는 기능
	수준 (3개)	① VOD 스트리밍만 제공 ② VOD 스트리밍 + 다운로드 (오프라인 시청 가능) ③ VOD 스트리밍 + 다운로드 (오프라인 시청 가능) + 라이브 스트리밍
5. 연동 가능 기기 종류 개수	설명	유료 OTT 서비스 가입시 이용 가능한 **기기의 종류 및 개수**(이용자 한명이 여러 기기에서 시청 가능)
	수준 (3개)	① 모바일 전용 (태플릿 포함) ② 모바일 (태플릿 포함) + PC ③ 모바일 (태플릿 포함) + PC + 스마트TV
6. 동시시청 가능 여부	설명	하나의 유료 계정으로 다수의 인원이 다수의 기기에서 동시 시청 가능 여부 (여러 명이 한 개의 계정에 여러 프로필을 생성하여 독립적으로 콘텐츠 시청이 가능함)
	수준 (2개)	① 가능함 ② 불가능함
7. 독점 콘텐츠 제공	설명	해당 플랫폼에서만 시청할 수 있는 콘텐츠를 제공하는지의 여부 (예: 넷플릭스 오리지널 영화 '옥자', 푹 월드컵 모바일 독점 생중계, 네이버 브이라이브 아이돌 생중계 등)
	수준 (2개)	① 제공함 ② 제공하지 않음
8. 요금제	설명	유료 OTT 서비스를 이용하는데 지불하는 월 이용요금
	수준 (3개)	① 6,000원/월 ② 10,000원/월 ③ 14,000원/월

다음 페이지부터 앞에서 설명 드린 유료 OTT 서비스 속성을 조합하여 구성한 **가상의 유료 OTT 서비스 유형의 선호 순위를 묻는 질문 8개가 제시**됩니다. (**제시한 유료 OTT 서비스 속성 이외의 다른 모든 속성은 서로 동일한 것으로 가정**하고 응답해 주십시오.)

문4. **(전체 응답자)** ① 제시한 가상의 3개의 유료 OTT 서비스 유형 중, **선호 순위를 1위부터 3위까지** 응답해 주시고,
② 선호하는 서비스 없음(비선택)이 포함된 4개의 유료 OTT 서비스 유형 중, **가장 선호하는 유형 하나에** O표해 주십시오.

▣ 유료 OTT 서비스 선호도 질문 1

OTT 서비스 속성 구분	유형 A	유형 B	유형 C	비선택
1. 서비스 제공자	플랫폼사업자	플랫폼사업자	방송사업자	선호하는 서비스 없음
2. 콘텐츠 다양성	100%	70%	70%	
3. 최대 화질	Full HD (HD 화질의 2배)	UHD 이상 (HD 화질의 8배)	HD 화질	
4. 시청 가능 형태	VOD 스트리밍 + 다운로드 + 라이브 스트리밍	VOD 스트리밍 + 다운로드	VOD 스트리밍 + 다운로드 + 라이브 스트리밍	
5. 연동 가능 기기 종류 개수	모바일 전용 + PC	모바일 전용 + PC + 스마트TV	모바일 전용 + PC + 스마트TV	
6. 독점 콘텐츠 제공	가능함	불가능함	가능함	
7. 동시시청 가능 여부	제공함	제공함	제공하지 않음	
8. 요금제	10,000원	14,000원	14,000원	
①**1위~3위** 선호순위 응답란	위	위	위	
②가장 선호하는 유형 1개 응답란	유형 **A**	유형 **B**	유형 **C**	비선택

▣ 유료 OTT 서비스 선호도 질문 2

OTT 서비스 속성 구분	유형 A	유형 B	유형 C	비선택
1. 서비스 제공자	플랫폼사업자	통신사업자	방송사업자	선호하는 서비스 없음
2. 콘텐츠 다양성	40%	100%	100%	
3. 최대 화질	Full HD (HD 화질의 2배)	HD 화질	HD 화질	
4. 시청 가능 형태	VOD 스트리밍 + 다운로드 + 라이브 스트리밍	VOD 스트리밍 + 다운로드 + 라이브 스트리밍	VOD 스트리밍 + 다운로드	
5. 연동 가능 기기 종류 개수	모바일만 가능	모바일 전용 + PC + 스마트TV	모바일 전용 + PC + 스마트TV	
6. 독점 콘텐츠 제공	가능함	불가능함	가능함	
7. 동시시청 가능 여부	제공함	제공함	제공하지 않음	
8. 요금제	14,000원	14,000원	10,000원	
①**1위~3위** 선호순위 응답란	위	위	위	
②가장 선호하는 유형 1개 응답란	유형 **A**	유형 **B**	유형 **C**	비선택

▣ 유료 OTT 서비스 선호도 질문 3

OTT 서비스 속성 구분	유형 A	유형 B	유형 C	비선택
1. 서비스 제공자	방송사업자	플랫폼사업자	방송사업자	선호하는 서비스 없음
2. 콘텐츠 다양성	70%	100%	100%	
3. 최대 화질	UHD 이상 (HD 화질의 8배)	UHD 이상 (HD 화질의 8배)	Full HD (HD 화질의 2배)	
4. 시청 가능 형태	VOD 스트리밍 + 다운로드 + 라이브 스트리밍	VOD 스트리밍만 제공	VOD 스트리밍만 제공	
5. 연동 가능 기기 종류 개수	모바일 전용 + PC	모바일 전용 + PC + 스마트TV	모바일 전용 + PC	
6. 독점 콘텐츠 제공	불가능함	불가능함	가능함	
7. 동시시청 가능 여부	제공함	제공하지 않음	제공하지 않음	
8. 요금제	6,000원	6,000원	14,000원	
①**1위~3위** 선호순위 응답란	위	위	위	
②가장 선호하는 유형 1개 응답란	유형 **A**	유형 **B**	유형 **C**	비선택

▣ 유료 OTT 서비스 선호도 질문 4

OTT 서비스 속성 구분	유형 A	유형 B	유형 C	비선택
1. 서비스 제공자	방송사업자	방송사업자	통신사업자	선호하는 서비스 없음
2. 콘텐츠 다양성	100%	40%	40%	
3. 최대 화질	UHD 이상 (HD 화질의 8배)	Full HD (HD 화질의 2배)	UHD 이상 (HD 화질의 8배)	
4. 시청 가능 형태	VOD 스트리밍 + 다운로드 + 라이브 스트리밍	VOD 스트리밍 + 다운로드	VOD 스트리밍만 제공	
5. 연동 가능 기기 종류 개수	모바일만 가능	모바일 전용 + PC + 스마트TV	모바일 전용 + PC + 스마트TV	
6. 독점 콘텐츠 제공	불가능함	가능함	가능함	
7. 동시시청 가능 여부	제공하지 않음	제공함	제공함	
8. 요금제	10,000원	6,000원	10,000원	
① **1위~3위** 선호순위 응답란	위	위	위	
② 가장 선호하는 유형 1개 응답란	유형 **A**	유형 **B**	유형 **C**	비선택

▣ 유료 OTT 서비스 선호도 질문 5

OTT 서비스 속성 구분	유형 A	유형 B	유형 C	비선택
1. 서비스 제공자	플랫폼사업자	통신사업자	방송사업자	선호하는 서비스 없음
2. 콘텐츠 다양성	40%	100%	70%	
3. 최대 화질	Full HD (HD 화질의 2배)	UHD 이상 (HD 화질의 8배)	Full HD (HD 화질의 2배)	
4. 시청 가능 형태	VOD 스트리밍 + 다운로드 + 라이브 스트리밍	VOD 스트리밍 + 다운로드 + 라이브 스트리밍	VOD 스트리밍 + 다운로드	
5. 연동 가능 기기 종류 개수	모바일 전용 + PC + 스마트TV	모바일만 가능	모바일만 가능	
6. 독점 콘텐츠 제공	불가능함	가능함	불가능함	
7. 동시시청 가능 여부	제공하지 않음	제공하지 않음	제공함	
8. 요금제	6,000원	6,000원	10,000원	
① **1위~3위** 선호순위 응답란	위	위	위	
② 가장 선호하는 유형 1개 응답란	유형 **A**	유형 **B**	유형 **C**	비선택

▣ 유료 OTT 서비스 선호도 질문 6

OTT 서비스 속성 구분	유형 A	유형 B	유형 C	비선택
1. 서비스 제공자	방송사업자	통신사업자	통신사업자	선호하는 서비스 없음
2. 콘텐츠 다양성	40%	40%	70%	
3. 최대 화질	UHD 이상 (HD 화질의 8배)	UHD 이상 (HD 화질의 8배)	Full HD (HD 화질의 2배)	
4. 시청 가능 형태	VOD 스트리밍만 제공	VOD 스트리밍 + 다운로드	VOD 스트리밍 + 다운로드	
5. 연동 가능 기기 종류 개수	모바일만 가능	모바일 전용 + PC	모바일 전용 + PC	
6. 독점 콘텐츠 제공	가능함	불가능함	가능함	
7. 동시시청 가능 여부	제공함	제공하지 않음	제공하지 않음	
8. 요금제	14,000원	14,000원	10,000원	
① **1위~3위** 선호순위 응답란	위	위	위	
② 가장 선호하는 유형 1개 응답란	유형 **A**	유형 **B**	유형 **C**	비선택

■ 유료 OTT 서비스 선호도 질문 7

OTT 서비스 속성 구분	유형 A	유형 B	유형 C	비선택
1. 서비스 제공자	통신사업자	플랫폼사업자	플랫폼사업자	선호하는 서비스 없음
2. 콘텐츠 다양성	100%	40%	70%	
3. 최대 화질	Full HD (HD 화질의 2배)	HD 화질	HD 화질	
4. 시청 가능 형태	VOD 스트리밍만 제공	VOD 스트리밍 + 다운로드	VOD 스트리밍만 제공	
5. 연동 가능 기기 종류 개수	모바일 전용 + PC + 스마트TV	모바일만 가능	모바일만 가능	
6. 독점 콘텐츠 제공	불가능함	가능함	불가능함	
7. 동시시청 가능 여부	제공함	제공하지 않음	제공함	
8. 요금제	6,000원	6,000원	10,000원	
① **1**위~**3**위 선호순위 응답란	위	위	위	
② 가장 선호하는 유형 1개 응답란	유형 **A**	유형 **B**	유형 **C**	비선택

■ 유료 OTT 서비스 선호도 질문 8

OTT 서비스 속성 구분	유형 A	유형 B	유형 C	비선택
1. 서비스 제공자	통신사업자	통신사업자	플랫폼사업자	선호하는 서비스 없음
2. 콘텐츠 다양성	40%	70%	70%	
3. 최대 화질	HD 화질	Full HD (HD 화질의 2배)	HD 화질	
4. 시청 가능 형태	VOD 스트리밍 + 다운로드 + 라이브 스트리밍	VOD 스트리밍만 제공	VOD 스트리밍만 제공	
5. 연동 가능 기기 종류 개수	모바일 전용 + PC	모바일만 가능	모바일 전용 + PC	
6. 독점 콘텐츠 제공	불가능함	불가능함	가능함	
7. 동시시청 가능 여부	제공함	제공하지 않음	제공하지 않음	
8. 요금제	10,000원	14,000원	6,000원	
① **1**위~**3**위 선호순위 응답란	위	위	위	
② 가장 선호하는 유형 1개 응답란	유형 **A**	유형 **B**	유형 **C**	비선택

Appendix 5: Discrete Choice Experiment questionnaire: Alternative Fuel Vehicle

Ⅲ. 자동차 유형별 선호도

다음은 자동차의 여러 속성과 속성별 수준에 대한 설명입니다. 다음 제시한 속성 설명을 잘 숙지하시고 응답해 주시기 바랍니다.

▣ 자동차 속성 및 수준 설명문

속성			속성 설명 및 수준
1. 연료 종류		설명	차량의 연료종류는 휘발유, 경유, LPG, 하이브리드, 전기, 수소연료전지로 구분됨 - 휘발유, 경유 차량은 일반적으로 액체연료인 유류만을 연료로 사용하는 내연기관차임 - 하이브리드 차량은 휘발유/경유을 기본으로 전기 모터로 주행을 보조하는 차량임 - LPG 차량은 기체연료를 액화한 액화석유가스를 연료로 사용하는 내연기관차임 - 전기 차량은 전기만을 연료로 사용하는 차량이며, 수소연료전지 차량은 수소를 주 연료로 사용하는 차량임
		수준 (5개)	① 휘발유 (하이브리드 포함) ② 경유 ③ LPG ④ 전기 ⑤ 수소연료전지
전기차 만 해당	1-1. 충전시간	설명	50% 수준까지 충전 시 걸리는 총 시간
		수준 (3개)	① 1시간 ② 2시간 ③ 4시간
전기차/수소차/LPG만 해당	1-2. 충전소 접근성	설명	주유/충전소 접근성은 소비자가 위치한 곳에서 주유/충전소까지의 평균 거리를 의미함. 현재 휘발유/경유 주유소 기준 50%, 70%, 100% 수준임. ※ 참고로, 휘발유/경유를 판매하는 일반 주유소까지의 평균거리는 약 2km임
		수준 (3개)	① 50% ② 70% ③ 90%
2. 차종		설명	차량의 종류를 나타냄, 경차/소형차/준중형차 (모닝, 아반떼, K3 등), 중형차 (소나타, K5, 말리부 등), 대형차 (그랜저, 제너시스 G80, G90 등), SUV/RV (카니발, 산타페, 코란도 등)
		수준 (4개)	① 경차/소형차/준중형차 ② 중형차 ③ 대형차 ④ SUV/RV
3. 연료비용(연비)		설명	10Km 주행 시 소요되는 비용 (연료비용은 국내운행 차량의 월평균 주행거리 1300km를 적용하여 계산함)
		수준 (4개)	① 500원/10km (65,000원/월) ② 1,000원/10km (130,000원/월) ③ 1,500원/10km (195,000원/월) ④ 2,000원/10km (260,000원/월)
4. 최대 주행가능거리		설명	1회 완전 주유/충전 시 운행할 수 있는 최대 주행 가능 거리 (전기차의 경우 겨울철엔 연비가 하락하여, 전기차의 겨울 주행거리는 10% 감소함.)
		수준 (3개)	① 300km ② 450km ③ 600km
5. 자율주행 수준		설명	차량 자율주행 기술 수준은 자율주행 기술 수준에 따라 자율주행기능 없음, 보조주행, 부분 자율주행 등으로 분류됨 - 자율주행기능 없음: 현재 상용화된 대부분의 자동차를 나타내며, 주행자가 직접 운전할 필요가 있음 - 주행보조기능: 주행자가 설정한 속도로 차선과 차 간격을 유지하며 주행할 수 있는 수준 - 부분자율주행 기능: 고속도로 및 혼잡하지 않은 도로에서 자동으로 주행할 수 있는 수준
		수준 (3개)	① 자율주행기능 없음 ② 주행보조기능 ③ 부분자율주행 기능
6. 차량 구입 가격		설명	차량 등록세, 취득세 등 구매 과정 중 세금을 포함한 차량 구매에 소요되는 총 비용을 의미함
		수준 (4개)	① 1,500만원 ② 3,000만원 ③ 4,500만원 ④ 6,000만원

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1. 앞 페이지에서 설명 드린 8개의 속성을 조합하여 구성한 **가상의 자동차 유형의 선호를 묻는 질문 8개가 제시됩니다.**
2. 귀하께서는 유형별 자동차 속성 수준을 잘 확인하시고,
   ① 선호하는 자동차 없음/현재 자동차 사용이 포함된 5개의 자동차 유형 중, **가장 선호하는 유형 하나에 O표**해 주시고,
   ② 선호하는 자동차 없음/현재 자동차 사용을 제외하고, **가장 선호하는 유형 선택 시 예상 교체시기**를 응답해 주십시오.
3. 각 유형에 제시된 8개의 속성 이외의 **다른 모든 자동차 속성은 서로 동일**한 것으로 가정하고 응답해주십시오.

문1. **(전체 응답자)** 다음 8개의 가상의 자동차 선호도 질문에 응답해 주십시오.

▣ 자동차 선호도 질문 1

속성	유형 A	유형 B	유형 C	유형 D	비선택
1. 연료 종류	LPG	전기	경유	수소연료전지	(자동차가 있는 경우) 현재 주사용 자동차 유지 / (자동차가 없는 경우) 구매하지 않음
1-1. 충전시간	-	2시간	-	-	
1-2. 충전소 접근성	50%	70%		50%	
2. 차종	경차/소형차/준중형차	SUV/RV	SUV/RV	SUV/RV	
3. 연료비용 (연비)	1,000원/10km	1,500원/10km	500원/10km	1,000원/10km	
4. 최대 주행가능 거리	450km	300km	450km	600km	
5. 자율주행 수준	자율주행기능 없음	부분자율주행 기능	자율주행기능 없음	주행보조기능	
6. 차량 구입 가격	1,500만원	4,500만원	4,500만원	3,000만원	
① 가장 선호하는 유형 (5개 중 하나에 O표 →)	유형 A	유형 B	유형 C	유형 D	비선택
② 선호하는 유형으로 예상 교체시기	☐ 년 후 ==================================== 0. 선호차량은 있으나 차량 교체는 하지않음				

▣ 자동차 선호도 질문 2

속성	유형 A	유형 B	유형 C	유형 D	비선택
1. 연료 종류	수소연료전지	경유	전기	전기	(자동차가 있는 경우) 현재 주사용 자동차 유지 / (자동차가 없는 경우) 구매하지 않음
1-1. 충전시간	-	-	4시간	1시간	
1-2. 충전소 접근성	50%	-	50%	50%	
2. 차종	대형차	중형차	대형차	중형차	
3. 연료비용 (연비)	1,500원/10km	2,000원/10km	2,000원/10km	500원/10km	
4. 최대 주행가능 거리	450km	600km	600km	450km	
5. 자율주행 수준	주행보조기능	주행보조기능	부분자율주행 기능	부분자율주행 기능	
6. 차량 구입 가격	6,000만원	4,500만원	6,000만원	4,500만원	
① 가장 선호하는 유형 (5개 중 하나에 O표 →)	유형 A	유형 B	유형 C	유형 D	비선택
② 선호하는 유형으로 예상 교체시기	☐ 년 후 ==================================== 0. 선호차량은 있으나 차량 교체는 하지않음				

▣ 자동차 선호도 질문 3

속성	유형 A	유형 B	유형 C	유형 D	비선택
1. 연료 종류	경유	휘발유	휘발유	수소연료전지	(자동차가 있는 경우) 현재 주사용 자동차 유지 / (자동차가 없는 경우) 구매하지 않음
1-1. 충전시간	-	-	-	-	
1-2. 충전소 접근성	-	-	-	90%	
2. 차종	대형차	중형차	경차/소형차/준중형차	중형차	
3. 연료비용 (연비)	1,500원/10km	1,000원/10km	1,500원/10km	500원/10km	
4. 최대 주행가능 거리	450km	300km	450km	300km	
5. 자율주행 수준	자율주행기능 없음	자율주행기능 없음	주행보조기능	주행보조기능	
6. 차량 구입 가격	4,500만원	3,000만원	1,500만원	4,500만원	
① 가장 선호하는 유형 (5개 중 하나에 O표 →)	유형 A	유형 B	유형 C	유형 D	비선택
② 선호하는 유형으로 예상 교체시기	☐ 년 후 ================================== 0. 선호차량은 있으나 차량 교체는 하지않음				

▣ 자동차 선호도 질문 4

속성	유형 A	유형 B	유형 C	유형 D	비선택
1. 연료 종류	전기	수소연료전지	LPG	경유	(자동차가 있는 경우) 현재 주사용 자동차 유지 / (자동차가 없는 경우) 구매하지 않음
1-1. 충전시간	4시간				
1-2. 충전소 접근성	70%	90%	70%		
2. 차종	대형차	경차/소형차/준중형차	중형차	경차/소형차/준중형차	
3. 연료비용 (연비)	2,000원/10km	1,500원/10km	1,500원/10km	2,000원/10km	
4. 최대 주행가능 거리	600km	450km	300km	300km	
5. 자율주행 수준	자율주행기능 없음	자율주행기능 없음	주행보조기능	부분자율주행 기능	
6. 차량 구입 가격	4,500만원	3,000만원	3,000만원	1,500만원	
① 가장 선호하는 유형 (5개 중 하나에 O표 →)	유형 A	유형 B	유형 C	유형 D	비선택
② 선호하는 유형으로 예상 교체시기	☐ 년 후 ================================== 0. 선호차량은 있으나 차량 교체는 하지않음				

▣ 자동차 선호도 질문 5

속성	유형 A	유형 B	유형 C	유형 D	비선택
1. 연료 종류	LPG	경유	휘발유	전기	(자동차가 있는 경우) 현재 주사용 자동차 유지 / (자동차가 없는 경우) 구매하지 않음
1-1. 충전시간	-	-	-	4시간	
1-2. 충전소 접근성	50%	-	-	90%	
2. 차종	중형차	SUV/RV	경차/소형차/준중형차	대형차	
3. 연료비용 (연비)	2,000원/10km	1,500원/10km	500원/10km	500원/10km	
4. 최대 주행가능 거리	450km	300km	600km	300km	
5. 자율주행 수준	부분자율주행 기능	자율주행기능 없음	주행보조기능	주행보조기능	
6. 차량 구입 가격	6,000만원	6,000만원	3,000만원	6,000만원	
① 가장 선호하는 유형 (5개 중 하나에 O표 →)	유형 A	유형 B	유형 C	유형 D	비선택
② 선호하는 유형으로 예상 교체시기	☐ 년 후 ================================== 0. 선호차량은 있으나 차량 교체는 하지않음				

■ 자동차 선호도 질문 6

속성	유형 A	유형 B	유형 C	유형 D	비선택
1. 연료 종류	LPG	수소연료전지	수소연료전지	전기	(자동차가 있는 경우) 현재 주사용 자동차 유지 / (자동차가 없는 경우) 구매하지 않음
1-1. 충전시간	-	-	-	4시간	
1-2. 충전소 접근성	70%	90%	70%	50%	
2. 차종	대형차	SUV/RV	대형차	중형차	
3. 연료비용 (연비)	2,000원/10km	2,000원/10km	1,000원/10km	1,500원/10km	
4. 최대 주행가능 거리	600km	600km	450km	300km	
5. 자율주행 수준	자율주행기능 없음	자율주행기능 없음	부분자율주행 기능	자율주행기능 없음	
6. 차량 구입 가격	4,500만원	3,000만원	4,500만원	1,500만원	
① 가장 선호하는 유형 **(5**개 중 하나에 O표 **→)**	유형 A	유형 B	유형 C	유형 D	비선택
② 선호하는 유형으로 예상 교체시기	☐ 년 후 ==================================== 0. 선호차량은 있으나 차량 교체는 하지않음				

■ 자동차 선호도 질문 7

속성	유형 A	유형 B	유형 C	유형 D	비선택
1. 연료 종류	LPG	경유	LPG	휘발유	(자동차가 있는 경우) 현재 주사용 자동차 유지 / (자동차가 없는 경우) 구매하지 않음
1-1. 충전시간	-	-	-	-	
1-2. 충전소 접근성	70%	-	70%	-	
2. 차종	대형차	SUV/RV	경차/소형차/준중형차	중형차	
3. 연료비용 (연비)	1,500원/10km	2,000원/10km	500원/10km	500원/10km	
4. 최대 주행가능 거리	450km	450km	300km	300km	
5. 자율주행 수준	주행보조기능	자율주행기능 없음	주행보조기능	자율주행기능 없음	
6. 차량 구입 가격	3,000만원	3,000만원	1,500만원	3,000만원	
① 가장 선호하는 유형 **(5**개 중 하나에 O표 **→)**	유형 A	유형 B	유형 C	유형 D	비선택
② 선호하는 유형으로 예상 교체시기	☐ 년 후 ==================================== 0. 선호차량은 있으나 차량 교체는 하지않음				

■ 자동차 선호도 질문 8

속성	유형 A	유형 B	유형 C	유형 D	비선택
1. 연료 종류	LPG	전기	경유	수소연료전지	(자동차가 있는 경우) 현재 주사용 자동차 유지 / (자동차가 없는 경우) 구매하지 않음
1-1. 충전시간	-	2시간	-	-	
1-2. 충전소 접근성	50%	70%	-	50%	
2. 차종	경차/소형차/준중형차	SUV/RV	SUV/RV	SUV/RV	
3. 연료비용 (연비)	1,000원/10km	1,500원/10km	500원/10km	1,000원/10km	
4. 최대 주행가능 거리	450km	300km	450km	600km	
5. 자율주행 수준	자율주행기능 없음	부분자율주행 기능	자율주행기능 없음	주행보조기능	
6. 차량 구입 가격	1,500만원	4,500만원	4,500만원	3,000만원	
① 가장 선호하는 유형 **(5**개 중 하나에 O표 **→)**	유형 A	유형 B	유형 C	유형 D	비선택
② 선호하는 유형으로 예상 교체시기	☐ 년 후 ==================================== 0. 선호차량은 있으나 차량 교체는 하지않음				

Abstract (Korean)

본 연구는 혜택기반모형에 혜택 척도 모수를 도입한 혜택척도모형을 제안한다. 혜택척도모형은 정보가 희소한 이산선택실험에서 데이터를 보다 효과적으로 사용할 수 있다는 장점이 있는데, 본 연구에서는 베이지안 학습 방법에 기반하여 의사결정 중요도 정보를 추출하여 모형 추정에 활용하고 구현하는 방법을 보였다. 제안한 혜택척도모형은 표준 다항로짓과 혜택기반모형보다 우수한 모형 적합도를 보였고, 우수한 예측력을 제공하였으며, 우수한 혜택 할당 확률의 수렴을 보였으며, 다른 해석을 제공하였다.

혜택척도모형을 확장한 색인혜택척도모형은 모형 적합도 수준에서 표준 다항로짓에서 개선이 없는 수준이었는데, 이는 속성을 혜택으로 할당되는 방식을 연구자가 가정하는 것에는 신중한 접근이 필요하며, 개인이 속성을 혜택으로 할당하는 방식이 실제로 이질적이라는 증거로 판단된다. 또한, 혜택척도모형에서 척도 모수에 인구통계변수를 포함하여 혜택 차원의 이질성을 포착할 수 있는 가능성을 확인하였다. 본 연구에서는 또한, 한계효용체감의 범위가 혜택 단위 뿐 아니라 전체 효용 단위로도 발생할 수 있음을 보였다.

주요어 : 이산선택모형; 혜택기반 컨조인트; 통합규칙; 한계효용체감; 척도 모수; 베이지안 러닝
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