Ph. D. Dissertation in Economics

Reference-Dependent Choice Model Based on Consistency and Context

- Focusing on Consumers' Different Preference Directions and Reference Points Shifting within a Random Utility Framework -

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이 논문을 경제학박사학위 논문으로 제출함

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Abstract

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In a standard (or neoclassical) economic model, such as the widely used discrete choice model for analyzing consumers' choices, respondents' preferences are assumed to be independent of reference points. However, in the actual decision-making process, consumers choose a product or service based on relative attribute levels, which depends on a reference point, rather than presented attribute levels of alternatives. With an emphasis on the reference point effect, which is an important aspect in heuristics, a concept related to behavior, consumer research in psycho-economics and behavioral economics has generally assumed reference-dependent preferences. Thus, a reference-

dependent choice model that integrates the reference-dependent utility function into the discrete choice model has been developed. The reference-dependent choice model is used to analyze consumers' asymmetric preferences for attributes of alternatives by including the loss aversion effect in the standard economic model. However, the existing reference-dependent choice model can be used to analyze only the asymmetric preferences of some attributes, such as time and cost, where consumers' preferred direction is the same. When analyzing attribute for which the preferred direction is different, the loss aversion parameter and the disparity between marginal willingness to accept and marginal willingness to pay derived from the existing reference-dependent choice model are inconsistent with economic definitions. Therefore, the first objective of this study is to propose a reference-dependent choice model with consistency, which can consider the reference-dependent theory when analyzing attributes regardless of the preferred directions. Next, according to consumer studies in economics, consumers make more efforts to avoid losses, yielding a context effect of evaluating the alternative centered on some important attributes constituting the alternative. Thus, when consumers are presented with an alternative that satisfies the reference point of attributes for which there is high importance of loss aversion, an incentive arises to shift the reference point of attributes for which there is relatively low importance of loss aversion. In other words, it is possible that the reference points of consumers are shifted in terms of the choice context. Nevertheless, the existing reference-dependent choice model relies on a fixed reference point framework, and studies have hitherto not incorporated the reference point

effect and the context effect on the discrete choice model. Therefore, the second objective of this study is to propose a reference points shifting rule using the relative importance of loss aversion, considering that consumers exert greater efforts to avoid an undesirable result. In addition, this study proposes an advanced reference-dependent choice model by integrating the reference points shifting rule to the reference-dependent choice model based on consistency. The advanced reference-dependent choice model is a method that better reflects the reality of the decision-making process, because it includes the reference point effect and context effect, which are the most important effects for heuristics. As a result, the methods presented in this study can improve the performance of empirical models and deepen understanding of consumers' behavior.

Keywords: Discrete choice model; Reference point effect; Loss aversion parameter; Reference-dependent model; Reference-dependent preferences; Context effect

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Chapter 1. Introduction

1.1 Research Background: Limitations of the Traditional and Alternative Consumer Theories

The "economic human" paradigm for decision-making in neoclassical economics has become a dominant approach to economics (Samuelson, 1947; Von Neumann & Morgenstern, 1944). Neoclassical economics, which is based on utility theory, has become part of mainstream economics along with Keynesian economics (Lawson, 1994).[1] In neoclassical economics, consumers are assumed to maximize utility based on complete information and rational preferences (Ding, Veeman, & Adamowicz, 2012). This neoclassical economics paradigm is still widely accepted by modern economists, but has been criticized from various aspects. The core of the criticism is the question of the behavioral reality of neoclassical consumer theory (Edwards, 1954; Simon, 1955; Tversky & Kahneman, 1974). In contrast to the complete rationality of neoclassical economics, cognitive psychology has proposed bounded (or limited) rationality, emphasizing that consumers' actual choice behavior is reference-dependent and context-dependent (Simon, 1955; Tversky & Kahneman, 1974). Consequently, behavioral economics, which integrates the insights of neoclassical economics and cognitive psychology, has emerged; it justifies its method and insight based mainly on improved

[1]Some scholars criticize the use of neoclassical economics terminology in the course of describing modern economics and mainstream economics (Colander, 2000), but in this study, neoclassical economics is still to be recognized as mainstream economics, because the discrete choice model, which is the basic framework of this study, is based on the random utility theory, which is the most widely used theory to analyze consumer choice.

model fit and empirical results (Berg & Gigerenzer, 2010; Rabin, 2002). Studies in behavioral economics have presented innovative methods across the social sciences by modeling the realistic choice behavior of consumers (Ariely, 2008; Kahneman, 2003; Starmer, 2000; Laibson & List, 2015; Tversky & Kahneman, 1991). The impact of behavioral economics on neoclassical consumer theory has already been significant (McFadden, 2007). The application and development of method that includes heuristics encompassing decision strategies into a neoclassical economic model (hereafter, the standard economic model) are required for a more sophisticated and meaningful analysis of consumer preferences (McFadden, 2001).

The behavior of consumers in neoclassical economics can be explained by the random utility maximization (RUM) model. The RUM refers to a model that maximizes utility and that includes stochastic factors (McFadden, 2001). The discrete choice model derived from the RUM based on the random utility theory (RUT) is a method suitable for analyzing consumer preferences for attributes that constitute alternatives, such as products, services, and policies (McFadden & Train, 2000; Small & Rosen; 1981). The discrete choice model primarily uses data obtained from discrete choice experiments based on stated preference (Adamowicz, Louviere, & Williams, 1994). Moreover, in the discrete choice experiment, consumers choose the preferred alternative or respond to the rank of the alternatives, and the discrete choice model explains the process (Hanley, Mourato, & Wright, 2001; Train, 2009). In the standard economic model, which analyzes the choice situation, including the discrete choice model, it is assumed that the preferences of consumers are independent of the reference point (Carson & Groves, 2007; Hardie, Johnson, & Fader, 1993; Tversky & Kahneman, 1991).

However, when considering the actual decision-making process, it has been found that consumers are highly influenced by reference points, such as current status (or status quo), when choosing alternatives (Tversky & Kahneman, 1991). Specifically, consumers judge gains (i.e., desirability and advantage) and losses (i.e., undesirability and disadvantage) by comparison with the reference points corresponding to the attributes of the alternative (Tversky & Kahneman, 1991; Van Osch, Van Den Hout, & Stiggelbout, 2006). In other words, consumers evaluate alternatives based on relative attribute levels that depend on a reference point, but not on the presented attribute level of the alternative. Thus, reference-dependent behavior, which has a significant effect on consumer preference, is called the reference point effect (Kahneman & Tversky, 1979); this effect is generally assumed in behavioral economics studies that analyze consumer preference (Dellavigna, 2009).

The reference point effect first appeared in prospect theory, which is the basis of behavioral economics. Prospect theory focuses on a single attribute in the presence of risk (Kahneman & Tversky, 1979). Subsequently, with the emergence of the reference-dependent theory, which focuses on multiple attributes in the absence of risk under the premise of prospect theory (Tversky & Kahneman, 1991), it is possible to analyze the reference-dependent preference relationships among the attributes constituting the alternative. Against this backdrop, the scope of studies analyzing the asymmetric preference and loss aversion effect of consumers has been extended from a single attribute and overall value (Derbaix, 1983) to multiple attributes (De Borger & Fosgerau, 2008).

As a result, behavioral economics developed a reference-dependent choice model incorporating the reference-dependent theory into the standard discrete choice model. The reference-dependent choice model was initially developed based on basic discrete choice models, such as the multinomial logit model (Hardie et al., 1993). Subsequently, the reference-dependent theory was developed and integrated with advanced discrete choice models, such as the mixed logit model and hierarchical Bayesian logit model (Kim, Lee, & Ahn, 2016; Kim, Park, & Lee, 2018). The main theories and models of economics and psychology related to consumer choice are shown in Figure 1. The reference-dependent choice model has many advantages in terms of consumer preferences analysis. In order words, the model can explain the disparity between the marginal willingness to accept (MWTA) and marginal willingness to pay (MWTP), which are important topics in economics through the loss aversion effect (Brown, 2005; Coursey, Hovis, & Schulze, 1987; Hanemann, 1991; Plott & Zeiler, 2005). Furthermore, the model can improve the model fit because it considers real behavior (Stathopoulos, & Hess, 2012), and provides unbiased estimates of consumers' behavior (Bateman, Day, Jones, & Jude, 2009).

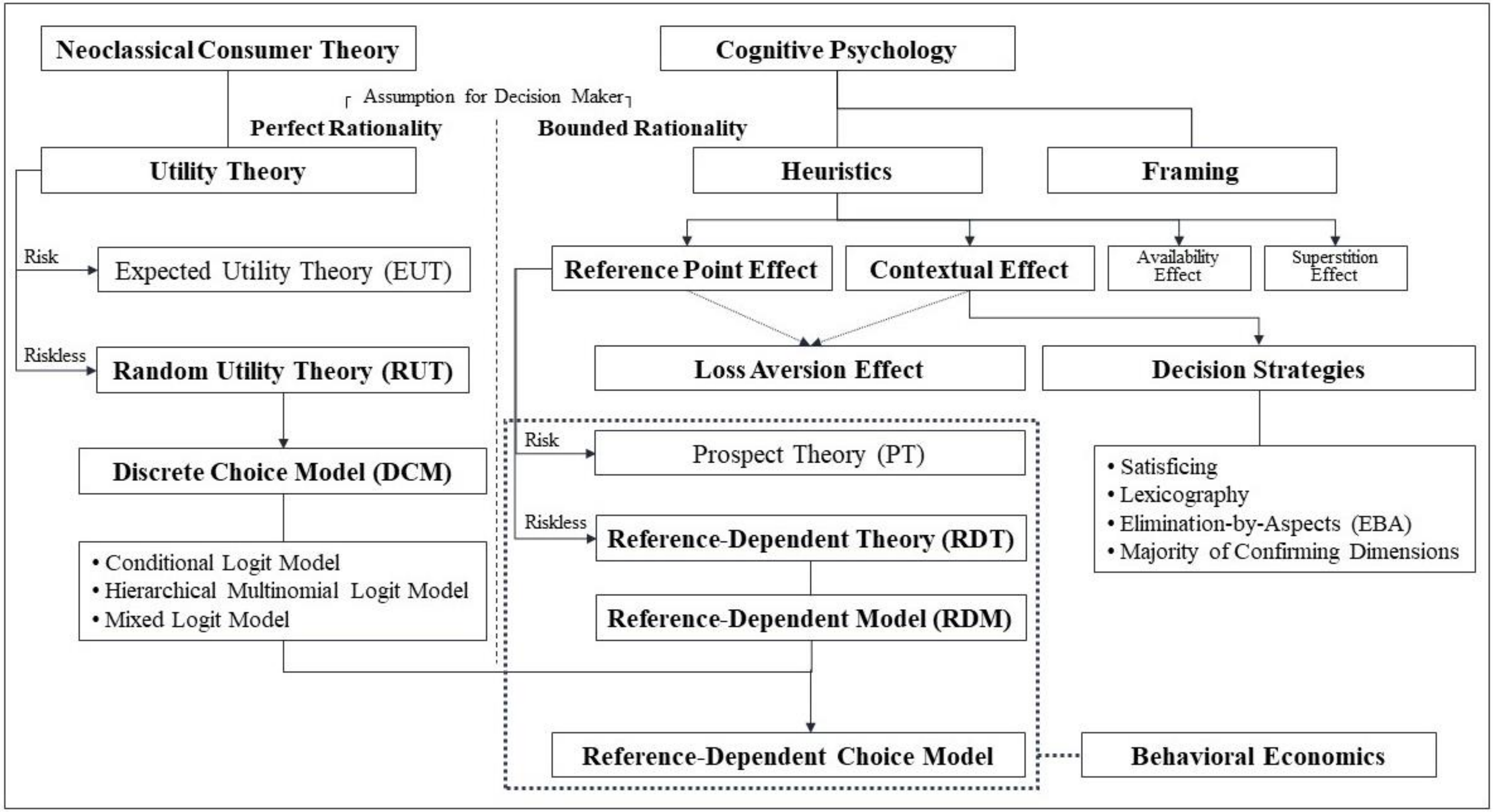

Figure 1. Key Theories and Models Related to Consumer Behavior of Neoclassical Economics, Cognitive Psychology, and Behavioral Economics

However, despite the importance of the reference point effect in the decision-making process, there is still a lack of modeling research for more sophisticated analysis of the asymmetric preference of a consumer. Against this backdrop, in addition to overcoming the limitations of the existing reference-dependent choice model, there is a need to consider the reality of behavior more comprehensively in the standard economic model while also considering the context effect, which is an important heuristic, as well as reference point effect, as shown in Figure 1. Specifically, there are inconsistent economic definitions of the loss aversion effect on the attributes for which the preferred direction is different in the existing reference-dependent choice model. Therefore, this study attempts to develop a consistent reference-dependent choice model that can consider the reference-dependent preferences for attributes regardless of the preferred directions of consumers.

In addition, one of the assumptions of the existing reference-dependent choice model is that consumers' reference points for attributes are fixed (Tversky & Kahneman, 1991). However, it is possible that a reference point that effectively explains consumers' behavior is shifting in a choice context (Loomes, Orr, & Sugden, 2009). The significance of the reference point effect and the context effect in heuristics (see Figure 1), which are considered to affect decision-making owing to the limited rationality of consumers, has been revealed in various studies. In addition, although there are some common characteristics through the concept of the loss aversion effect, there is no study that integrates these effects. In other words, the existing reference-dependent choice model has limitation in that it partly reflects the reality of behavior. Therefore, this study proposes a reference points shifting rule based on decision strategy theories for decision-making and develops an advanced reference-dependent choice model that integrates the reference points shifting rule into a consistent reference-dependent choice model. The limitations of the existing reference-dependent choice model and the outline of the developed model are presented in the following Section 1.2.

1.2 Research Objectives

1.2.1 Reference-Dependent Choice Model with Consistency

A reference-dependent choice model of behavioral economics incorporating the reference point effect, which is one of the major heuristics of cognitive psychology, is applied to the discrete choice model based on the RUT of neoclassical economics. This reference-dependent choice model can analyze the asymmetric preference of a consumer for the attributes constituting the alternative. However, when simply classifying the relative attribute level into an increase and decrease of attributes for which the preferred direction of consumers is different, using the existing reference-dependent choice model, the estimated results might not be consistent with the economic definitions related to the reference point effect. The research results of Kim, Lee, and Ahn (2016) and Kim, Park, and Lee (2018) are presented as follows to explain this in detail.

(i) *Of the attributes, 66.4% of consumers prefer smartphones with larger screens, while 33.6% prefer smaller ones. In this case, the following questions can be raised when applying the existing reference-dependent choice model. Can researchers judge the case in which the relative level of screen size compared to the reference point decreases as a loss? If not, can the case in which the level increases be considered as a loss? (Kim et al., 2016)*

(ii) The proportion of people who prefer to increase the power generation share of renewable energy is 69.3%, while that of people who prefer to decrease the share is 30.8%. In this case, the following questions can be asked when applying the existing reference-dependent choice model. Can researchers conclude that the case in which the level of renewable energy's share of power generation share decreases relative to the reference point is a loss? If not, can the case in which the level increases be considered as a loss? (Kim et al., 2018)

The reference-dependent preference leads to a loss aversion parameter for the attribute of the alternative, which has implications for the disparity between MWTA and MWTP. In this regard, the economic definition of the loss aversion parameter is as follows.

Loss aversion parameter: The ratio of the parameter estimates for the relative attribute level evaluated as a loss (or disadvantage) to the estimate for the relative attribute level evaluated as a gain (or advantage) (Kahneman & Tversky, 1979)

This is explained in more detail in Chapter 2, but in overview, if the loss aversion parameter is calculated using Equation (1), which expresses a simple asymmetric form of the existing reference-dependent choice model, Equation (2) can be derived.

Existing reference-dependent choice model Equation:

$$V(x \mid r)_j = \sum_k \beta_k^+ x_{jk(inc)} + \sum_k \beta_k^- x_{jk(dec)} \quad \text{Eq. (1)}$$

Loss aversion parameter equation:

$$\lambda_k = -\beta_k^- / \beta_k^+ \;\; or \;\; -\beta_k^+ / \beta_k^- \quad \text{Eq. (2)}$$

The loss aversion parameter can be derived through $-\beta_k^- / \beta_k^+$ of Equation (2) if increasing relative level of attributes is preferred, as in Equation (2), or $-\beta_k^+ / \beta_k^-$ of Equation (2) for the opposite case. In the abovementioned examples (i) and (ii), where the rate of preference for increasing the relative level of the attribute is greater than the rate for decreasing the relative level, if the loss aversion parameter is set to $-\beta_k^- / \beta_k^+$, then 33.6% of example (i) and 30.8% of example (ii) are contradict the definition of the loss aversion parameter. In addition, in the analysis of the existing reference-dependent choice model for attributes with different preference directions that ignore this contradiction, there is a limitation that the statistical significance of the parameter estimates cannot be guaranteed. Thus, in order to consider consistent reference-dependent preferences, the preference heterogeneity of consumers for specific attributes should be captured, and it should be modeled considering the preferred directions as well as the relative attribute level.

Figure 2 shows the indifference curves of consumers for attributes for which the preferred direction is different. Here, the indifference curve of consumer n_1, who prefers an increase in the attribute level, is on the left, and the indifference curve of consumer n_2, who prefers a decrease in the attribute level, is on the right. Furthermore, the reference points of consumers n_1 and n_2 are assumed as r and r'. If the relative level of attribute x increases by the same amount Δx (see Figure 2) in the case of consumer n_1, even if the price increases by Δp, utility remains the same. However, to maintain the utility of consumer n_2 as is, the price must decrease by $\Delta p'$. Thus, if the MWTA and MWTP of consumers n_1 and n_2 are expressed using Equation (1), the following Equations (3) and (4) are derived (Hensher, Shore, & Train, 2005; Shogren, Shin, Hayes, & Kliebenstein, 1994). However, when using the existing reference-dependent choice model for attributes for which the preferred direction is different, MWTA and MWTP follow Equation (5), and thus, it is obvious that inconsistent results would be derived as the loss aversion parameter. Therefore, the first objective of this study is to propose a reference-dependent choice model with consistency, which can consider the reference-dependent theory for the attributes for which the preferred direction of consumers is different.

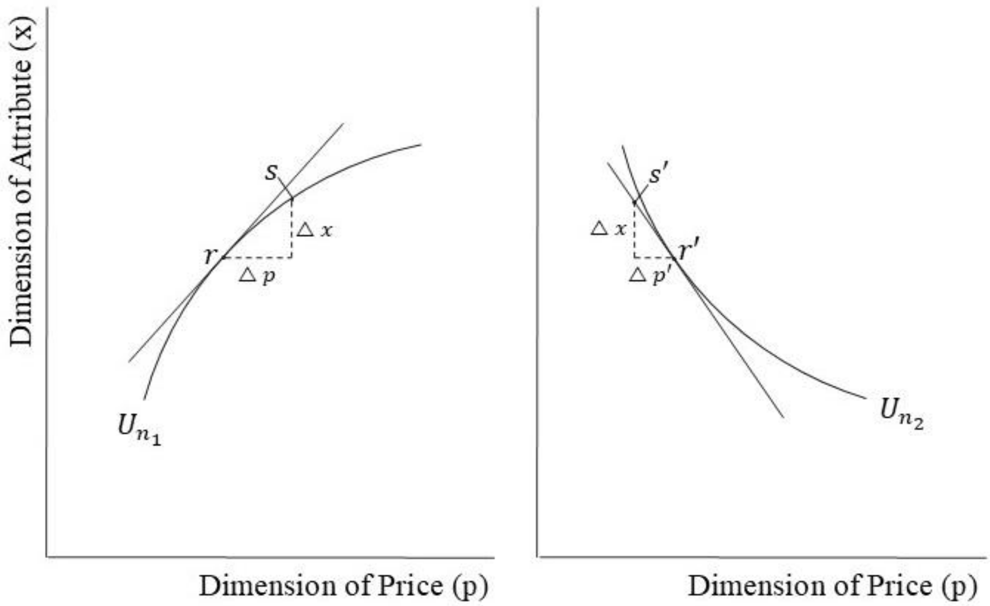

Figure 2. Indifference Curves of Attributes with Different Preference Directions

MWTA and MWTP of consumers with different preference directions:

- *MWTA and MWTP of respondent* n_1*, who prefers an increase in attribute* x

$$MWTA_k = -\beta_k^- / \beta_p^-, \ MWTP_k = -\beta_k^+ / \beta_p^+ \quad \cdots\cdots \text{Eq. (3)}$$

- *MWTA and MWTP of respondent* n_2*, who prefers a decrease in attribute* x

$$MWTA_k = -\beta_k^+ / \beta_p^-, \ MWTP_k = -\beta_k^- / \beta_p^+ \quad \cdots\cdots \text{Eq. (4)}$$

MWTA and MWTP using the existing reference-dependent choice model

$$MWTA_k = -\beta_k^- / \beta_p^- (or \ -\beta_k^+ / \beta_p^-), \ MWTP_k = -\beta_k^+ / \beta_p^+ (or \ -\beta_k^- / \beta_p^+) \ \cdots \text{Eq. (5)}$$

1.2.2 Reference-Dependent Choice Model with Context

Another feature of the existing reference-dependent choice model is the use of a fixed reference point framework (Tversky & Kahneman, 1991). As Figure 1 in Section 1.1 shows, the context effect as well as the reference point effect are the key concepts that constitute heuristics (McFadden, Machina, & Baron, 1999). If consumers encounter complex situations or there are relatively less important attributes of the alternative, consumers' preferences and judgments can change and depend on the choice context (Ariely, Loewenstein, & Prelec, 2003; Huber, Payne, & Puto, 1982; Tversky & Simonson 1993). As a result, since it is possible that the reference point is not fixed and may change with the choice context (Ariely et al., 2003; Loomes et al., 2009), a reference-dependent choice model that integrates the reference point effect and context effect is required.

When reference points shifting occurs, the domains of losses and gains change. However, since there are no studies consider reference points shifting in the choice experiment, no proper case study has been conducted, although this feature can be easily observed in actual consumers' choice behavior[2]. If the reference point is hard, the application of the fixed reference point framework is appropriate, so that the precondition of a shifting reference point is a soft reference point. To provide experimental evidence related to the soft reference point, an experiment was conducted through the following

[2]For instance, let us assume a situation in which a consumer purchases a new smartphone. The consumer currently posseses an Apple brand smartphone and paid 800,000 KRW for it. Furthermore, the consumer's importance of loss aversion for the brand is higher than that of price. In the process of choosing a new smartphone, an alternative to the Apple brand is presented at price of 830,000 KRW. In this case, if the fixed reference point framework is applied, the relative price level corresponds to the loss domain. However, the consumer who avoids the loss of the Apple brand has an incentive to shift the reference price, in which case, the consumer might not evaluate the relative price as a loss.

questionnaire. First, 350 respondents were asked about the reference point of telemedicine service attributes, and the corresponding reference points were to respond to the expected minimum level (Cantillo & Ortúzar, 2005; Swait 2001).

Q1. What is the expected minimum level for monthly service charge?

Q2. What is the expected minimum level for medical treatment cost?

Q3. What is the expected minimum level for response time?

Then, the choice experiment was conducted five times for each respondent. The experiment combined six attributes, including three attributes that were measured by questionnaire. Consumers with consistency should not choose the alternative if they include attributes that do not satisfy the expected minimum level, and if all alternatives included in the choice set contain attributes that do not satisfy the expected minimum level, then the no-choice option should be the response. In the analysis, 1426 of the 1750 observations (350 * 5 choice sets) were found to violate the reference point, and the share was very high (81.5%). In particular, the share of choices that violate two expected minimum levels that are reference points was also high (33.8%).

This result is because consumers generally consider multiple attributes rather than a single attribute in evaluating alternatives, which is why the reference point, the minimum expectation level for attributes, is violated (Swait, 2001; Tversky & Kahneman, 1991). Therefore, the results of this experiment show that consumers choose alternatives that give them the highest utility considering various attributes (Hensher & Johnson, 1981; Lancaster, 1966), and the reference point is soft rather than hard in a choice context (Swait, 2001). In other words, the reference point is not fixed and could shift. Therefore, the second objective of this study is to propose a reference points shifting rule based on loss aversion and decision strategy theory and an advanced reference-dependent choice model that integrates the reference point effect and context effect.

The estimates of the reference-dependent choice model considering the reference points shifting rule differ from those of the reference-dependent choice model of a fixed reference point framework. To explain this, the utility curve on attribute x and the price p of consumer n, who prefers a decrease in the relative level of attribute x, is used. For this utility curve, it is assumed that the parameters for the preference domain equal one and the loss aversion parameter of attribute x is larger than the loss aversion parameter of price p. Furthermore, assuming that the utility curve is linear (Tversky & Kahneman, 1991), the indifference curve of attribute x and price p is expressed as Figure 3.

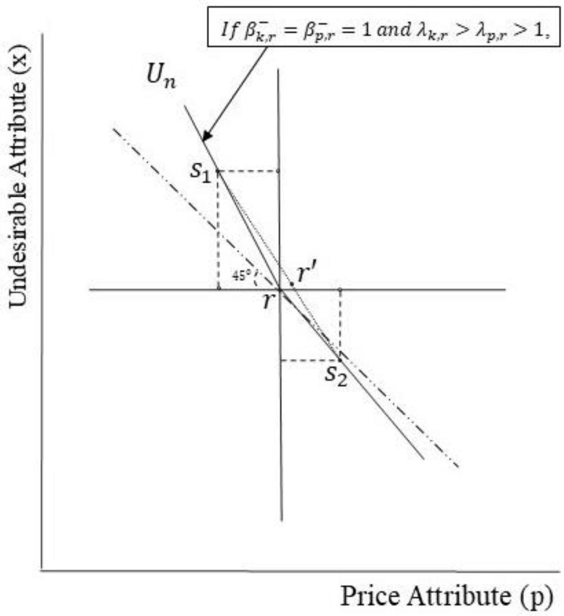

Figure 3. Indifferent Curves and Reference Points Shifting

Here, if consumer n considers the loss aversion of the other attribute as more important than attribute x and price p, the reference point is shifted from r to r'. If the loss aversion parameter, MWTA, and MWTP at reference point r are expressed using Equations (2) and (4), Equation (6) can be derived. Furthermore, if the reference point is shifted to r', as shown in Figure 3, the loss aversion parameter of attribute x decreases and the loss aversion parameter of price p increases. Moreover, as Equation (7) expresses, with regard to the ratio of MWTA to MWTP at reference point r' based on the degree of change of the loss aversion parameter, there may be a difference with the corresponding ratio value at reference point r. Therefore, in this study, the estimates of key economic concepts that can be explained by the loss aversion effect as well as the goodness-of-fit for proposed models in empirical studies are closely examined.

$$\lambda_{k,r} = -\beta^{+}_{k,r} / \beta^{-}_{k,r}, \ \lambda_{p,r} = -\beta^{+}_{p,r} / \beta^{-}_{p,r}, \quad MWTA_k = -\beta^{+}_{k,r} / \beta^{-}_{p,r}, \ MWTP_k = -\beta^{-}_{k,r} / \beta^{+}_{p,r} \qquad \text{Eq. (6)}$$

$$\begin{aligned} \lambda_{k,r'} &= -\beta^{+}_{k,r'} / \beta^{-}_{k,r'}, \ \lambda_{p,r'} = -\beta^{+}_{p,r'} / \beta^{-}_{p,r'} \\ MWTA_k / MWTP_k &= (-\beta^{+}_{k,r'} / \beta^{-}_{p,r'}) / (-\beta^{-}_{k,r'} / \beta^{+}_{p,r'}) \\ &= (-\beta^{+}_{k,r'} / \beta^{-}_{k,r'}) \times (-\beta^{+}_{p,r'} / \beta^{-}_{p,r'}) = \lambda_{k,r'} \times \lambda_{p,r'} \end{aligned} \qquad \text{Eq. (7)}$$

In this study, the framework for analyzing the asymmetric preference of consumers is summarized as follows. First, I investigate the preferred directions of consumers for each attribute that constitutes an alternative. To do this, I analyze the consumer preference using the mixed logit model, which is a typical discrete choice model. Second, along with the preferences of these consumers, I estimate the parameters of the preference domain and the non-preference domain of the relative levels of the consumers using the difference between the presented attribute level and the corresponding reference point, and I analyze the loss aversion parameter and the asymmetric preference using the estimates of parameters. Third, I establish a consumer's reference points shifting rule based on the theories of loss aversion and decision strategies, which is then included in the reference-dependent choice model for sophisticated analysis of the consumer's choice behavior.

1.3 Research Outline

This rest of this dissertation proceeds as follows. In Chapter 2, I first introduce a discrete choice model based on utility theory of neoclassical economics and examine prospect theory, the reference-dependent theory, and a reference-dependent model based on the reference point effect, which is one of the important heuristics of cognitive psychology. Then, I introduce the reference-dependent choice model of behavioral economics, which considers reference-dependent preference in the discrete choice model, and I discuss the limitations of the existing reference-dependent choice model. In addition, I review existing literature related to the context effect, which is one of the important heuristics and key decision strategies that illustrate the context effect. Finally, I discuss the limitations of the existing reference-dependent choice model and clarify the motivation for the development of the advanced methods to overcome the limitations. In Chapter 3, I propose a reference-dependent choice model that can consistently consider the asymmetric preferences for attributes for which the preferred direction is different. I also set a reference points shifting rule considering the context effect and loss aversion, and I propose a more realistic advanced reference-dependent choice model. In Chapter 4, I empirically analyze consumers' preferences for smartphones in the field of marketing; vehicles, including electric vehicles, in the energy sector; and telemedicine services in the health sector. First, these studies aim to prove goodness-of-fit and validity of the proposed models. In addition, prior to the empirical studies, to extend the reference-dependent choice model, I discuss brand loyalty, switching costs, and peer effect related to the endowment effect explained by the loss aversion effect. I also discuss the acceptability of introducing of innovative technologies related to the status quo effect. In Chapter 5, I summarize the contents of this study, describe its contributions and limitations, and propose future research directions.

Chapter 2. Literature Review

In this chapter, I first review the major discrete choice models that are widely used as econometrics for consumers' preference analysis. In particular, I focus on the mixed logit model, which can consider the preference heterogeneity of consumers. I then examine the existing reference-dependent choice model, which reflects the reference point effect, which is emphasized in prospect theory and the reference-dependent theory. Next, I discuss the context effect and the main decision strategies as important heuristics in the decision-making process along with the reference point effect. In the last section, I review the limitations of the existing reference-dependent choice model and mention the need for a reference points shifting rule that considers the context effect as well as the reference point effect. In this chapter, after discussing the development process and limitations of the existing reference-dependent choice model, I focus on explaining the direction and necessity of for developing the method.

2.1 Traditional Consumer Choice Theory and Model

Traditional consumer behavior studies primarily use a discrete choice model based on a utility maximization approach, known as RUT, to understand consumers' preferences for new technologies, products, and services (Chorus, 2012). In particular, the discrete choice model is a method used to model respondents' choices, analyze their preferences, and predict demand (Train, 2009). In the RUT, it is assumed that consumers choose alternatives that offer the highest utility to them and act rationally to maximize their utility (Hensher & Johnson, 1981; McFadden, 1986). The RUT, which is the theoretical foundation of the discrete choice model, is chosen because the behavior of consumers cannot be expressed solely by deterministic factors (Román & Martín, 2016). As consumers in the RUM model do not have complete information about their utility (Manski, 1977; McFadden, 1973), the utility of the consumers is expressed as the sum of deterministic and stochastic terms (Román & Martín, 2016).

The discrete choice model explains the choice of consumers mainly by using the data obtained from the discrete choice experiment. This experiment is used because the utility of consumers is derived not from the alternative itself but from the various attributes that constitute the alternative (Lancaster, 1966). In other words, monetary attributes, such as price and cost, and quality attributes, such as brand and performance, determine the utility of consumers (Thaler, 1980). As the discrete choice model is based on utility theory of neoclassical economics (Lowson, 1994), consumers facing the choice task are assumed to have rational and complete information (Manski, 1977). Moreover, as consumers choose alternatives that maximize their utility in a set of alternatives (Train, 2009), in the RUT, the utility maximization behavior rule is applied as the decision rule. This behavior rule generally refers to a compensatory decision process; the concept is that consumers make trade-offs between attributes when choosing alternatives that offer the highest utility (McFadden & Train, 2000).

2.1.1 Standard Logit Model

In the standard logit model, which provides the basis for the discrete choice model, it is represented that respondents' preferences for attributes are homogeneous through fixed parameters (McFadden, 1973; Train, 2009). However, if the heterogeneous preferences of the respondents are not considered, the explanatory power of the model decreases and can lead to biased estimation results (Bhat, 1997). Because such an analysis can provide false implications (Allenby, Arora, & Ginter, 1998), the standard logit model is evaluated to have limitations in capturing respondents' behavior and modeling demand (Keane & Wasi, 2013). Despite these limitations, the standard logit model is still widely used because the likelihood can be estimated relatively easily by the traditional (or conventional) maximum likelihood estimation method, as the choice probability takes a closed form (Train, 2009).

The discrete choice model, including the standard logit model, is based on the RUT, and the utility U_{nj} obtained by respondent n from alternative j in the random utility maximazation model is shown in Equation (8) (McFadden, 1973; Train, 2009).

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \beta_k^{'} x_{jk} + \varepsilon_{nj} \quad \cdots\cdots \text{Eq. (8)}$$

Here, the utility of individual respondents is separated into the deterministic term (V_{nj}), which can be observed and explained, such as product attributes and demographic characteristics, and the stochastic term (ε_{nj}), which cannot be observed and exists with uncertainty. Furthermore, the deterministic term can be expressed as the product of level vector x_k of attribute k, which constitutes an alternative j and parameter vector β_k, which represents the marginal utility of attribute k.

In addition, the discrete choice model can be classified according to the assumption of the stochastic term, but generally, stochastic term ε_{nj} is assumed to be an independently and identically distributed (iid) type-I extreme value. In this case, the density of stochastic term ε_{nj} can be defined as Equation (9) (Train, 2009).

$$f(\varepsilon_{nj}) = e^{-\varepsilon_{nj}} e^{e^{-\varepsilon_{nj}}} \quad \text{Eq. (9)}$$

Depending on the utility maximization rule, the choice probability P_{nj}, for which respondent n chooses alternative j that provides the highest utility within the choice set, is derived as in the following Equation (10) (Train, 2009).

$$\begin{aligned} P_{nj} &= P(U_{nj} > U_{ni},\ \forall j \neq i) \\ &= P(V_{nj} + \varepsilon_{nj} > V_{ni} + \varepsilon_{ni},\ \forall j \neq i) \\ &= P(\varepsilon_{ni} < \varepsilon_{nj} + V_{nj} - V_{ni},\ \forall j \neq i) \end{aligned} \quad \text{Eq. (10)}$$

Using Equation (9), which is the density of the stochastic term, Equation (10) which is the choice probability, can be derived to a closed form as Equation (11) (Train, 2009).

$$P_{nj} = \int \left(\prod_{j \neq i} e^{e^{-(\varepsilon_{nj} + V_{nj} - V_{ni})}} \right) e^{-\varepsilon_{nj}} e^{e^{-\varepsilon_{nj}}} d\varepsilon_{nj} = \frac{e^{V_{nj}}}{\sum_i e^{V_{ni}}} = \frac{e^{\beta_k^{'} x_{jk}}}{\sum_i e^{\beta_k^{'} x_{ik}}} \quad \text{······················Eq. (11)}$$

If there are multiple choice sets s presented to a respondent, the likelihood of respondent n choosing the alternative is expressed in Equation (12) (Train, 2009). Here, if respondent n chooses alternative j within choice set s, it is defined as $y_{njs} = 1$, otherwise as $y_{njs} = 0$.

$$P_n = \prod_s \prod_j (P_{njs})^{y_{njs}} \quad \text{······································Eq. (12)}$$

Assuming that each respondent's choice is independent of the choices of other respondents, the likelihood of a sample is expressed as the following Equation (13) (Train, 2009).

$$Likelihood = \prod_{n=1}^{N} P_n = \prod_{n=1}^{N} \prod_s \prod_j (P_{njs})^{y_{njs}} \quad \text{··························Eq. (13)}$$

Thus, although the standard logit model cannot reflect respondents' preference heterogeneity, it is still widely used given the ease of estimation. However, in the standard logit model, independence from irrelevant alternatives (IIA) characteristics are assumed, in which the ratio of the choice probabilities of the alternatives is the same regardless of the changes of attributes and attribute levels of the alternative, and this is an unrealistic assumption in many situations (Train, 2009). The limitations of this standard logit model can be avoided by incorporating heterogeneity of preference into the standard logit model. Thus, most recent studies using discrete choice models have adopted a mixed logit model that allows respondents' preference heterogeneity.

2.1.2 Mixed Logit Model

The mixed logit model has the advantage of not requiring the IIA assumption mentioned in Section 2.1.1 (McFadden & Train, 2000; Train, 1998; Train, 2009). Specifically, the mixed logit model overcomes the limitations of the standard logit model by introducing a continuous distribution to parameters β_k of the standard logit model to allow for individual heterogeneity (Train, 2009). Here, the probability distribution of each parameters is set by the researcher (Rigby & Burton, 2006), and normal, log-normal, triangular, and uniform distribution are mainly used (Hensher, Rose, & Greene, 2005). Thus, the mixed logit model simultaneously takes the form of random parameter logit model and error component logit model (Brownstone & Train, 1998; Train, 2009).

In the mixed logit model, if the parameters for the attributes (e.g., price and time) for which a preferred direction of consumers is determined to be certain are set as normal distributions, unrealistic results may be obtained. Thus, researcher often set the parameters of the attributes as log-normal distributions. However, in this case, there is a limitation that the variance of the parameter may be unrealistically large owing to the fat tails characteristic of the log-normal distribution (Patil, Burris, & Shaw, 2011). Thus, in most mixed logit model studies, it is assumed that the parameters follow a normal distribution with mean b and variance W. The utility obtained by respondent n from alternative j in the mixed logit model that sets the parameter with a normal distribution is shown in the following Equation (14) (McFadden & Train, 2000). Here, researchers generally assume that the stochastic term of the mixed logit model follows the iid type-I extreme value distribution, like the assumption of the standard logit model.

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \beta_n^{'} x_{jk} + \varepsilon_{nj}$$
$$\beta_n \sim N(b, W) \quad \text{Eq. (14)}$$

In the mixed logit model, the choice probability is the integration of the standard logit probability over density $f(\beta_n | b, W)$ as shown in the following Equation (15) (Train, 2009). Here L_{nj} is the logit probability estimated from parameter β_n and is given by Equation (16).

$$P_{nj} = \int L_{nj}(\beta_n) f(\beta_n | b, W) d\beta_n \quad \text{Eq. (15)}$$

$$L_{nj}(\beta_n) = \frac{e^{V_{nj}}}{\sum_i e^{V_{ni}}} = \frac{e^{\beta_{nk}^{'} x_{jk}}}{\sum_i e^{\beta_{nk}^{'} x_{ik}}} \quad \text{Eq. (16)}$$

If there are multiple choice sets s presented to a respondent, the likelihood of respondent n choosing the alternative is expressed in Equation (17) (Train, 2009). Here, as with the standard logit model of Section 2.1.1, if respondent n selects alternative j within choice set s, it is defined as $y_{njs} = 1$, and otherwise as $y_{njs} = 0$.

$$P_n = \int \prod_s \prod_j \left\{ L_{njs}(\beta_n) \right\}^{y_{njs}} f(\beta_n \mid b, W)\, d\beta_n \quad \cdots\cdots \text{Eq. (17)}$$

Furthermore, assuming that each respondent's choice is independent of the choices of other respondents, the likelihood of a sample is expressed as in Equation (18) (Train, 2009).

$$Likelihood = \prod_{n=1}^{N} P_n = \int \prod_{n=1}^{N} \prod_s \prod_j \left\{ L_{njs}(\beta_n) \right\}^{y_{njs}} f(\beta_n \mid b, W)\, d\beta_n \quad \cdots\cdots \text{Eq. (18)}$$

The mixed logit model can reflect the preferences heterogeneity at the individual level by assuming that the vector of parameters follows a continuous distribution, but since the choice probability is not a closed form, it cannot be estimated by the traditional maximum likelihood estimation method, unlike the standard logit model can (Train, 2009). In other words, a relatively complex simulated maximum likelihood estimation or Bayesian estimation method should be used to estimate the mixed logit model. In particular, if the Bayesian estimation method is used, individual-level parameters can be derived (Aravena, Martinsson, & Scarpa, 2014). Furthermore, the Bayesian estimation method has the following advantages. First, it can overcome the problem of initial value whereby the maximization result differs based on the initial value selection, and second, consistency and efficiency can be achieved in conditions that are more flexible (Train & Sonnier, 2005). Lastly, the estimation results can be interpreted in both Bayesian and traditional perspectives. Thus, the Bayesian estimation method is widely used to estimate the mixed logit model (Edwards & Allenby, 2003).

The mixed logit model is evaluated as an excellent tool to analyze the data obtained from the discrete choice experiment (Hensher & Greene, 2003; Rigby & Burton, 2006). In particular, the mixed logit model has been found to be superior to the standard logit model in terms of overall model fit and welfare estimation accuracy (Brouwer, Dekker, Rolfe, & Windle, 2010; Provencher & Bishop 2004). In addition to explaining the preference heterogeneity of consumers, the mixed logit model can be used for modelling the repeated responses of consumers. Furthermore, it can be used to modify the error structures and to accommodate the heteroscedasticity (i.e., uneven variance) that occurs when using various sources (Bhat & Castelar 2002; Brownstone & Train 1999; Greene & Hensher 2007; Hensher, Rose, & Greene. 2008).

2.1.3 Hierarchical Bayesian Logit Model

The hierarchical Bayesian logit model reflects respondents' heterogeneity by setting parameter vector β_n in the RUM model to be different for each respondent (Allenby & Rossi, 1998). Specifically, parameter vector β_n is expressed as in the following

Equation (19).

$$\beta_n = \Gamma \mathbf{z_n} + \zeta_n$$
$$\zeta_n \sim N(0, \Sigma) \quad \text{Eq. (19)}$$

Here, $\mathbf{z_n}$ is the vector representing the characteristics of individual respondents n, Γ is the vector matrix of the parameter corresponding to $\mathbf{z_n}$, ζ_n as stochastic terms represents the respondents' unobserved heterogeneity, and Σ is the vector matrix that represents the covariance between parameters β_n (Allenby & Ginter, 1995).

Bayesian analysis generally estimates the posterior distribution of each parameter by combining the prior distribution for each parameter with the likelihood determined by the data (Allenby & Ginter, 1995). Here, Equation (19) serves as a prior distribution for parameter β_n, and to complete the hierarchical Bayesian logit model, the prior distribution of Γ and Σ must be set. Thus, as in Equation (20) below, it is assumed that Γ follows a normal distribution, and Σ follows an inverse-Wishart distribution (Allenby & Ginter, 1995).

$$\Gamma \sim N(a, A)$$
$$\Sigma \sim W(w, W) \quad \text{Eq. (20)}$$

In addition, Markov chain Monte Carlo (MCMC) simulation is required to estimate the hierarchical Bayesian logit model. The MCMC method is an approach of deriving a distribution that converges to the posterior distribution of each parameter by repeating probability extraction by taking parameters as conditions, and uses Gibbs sampling, which is a typical extraction technique (Train, 2009). In the estimation of the hierarchical Bayesian logit model, the MCMC method consists of three steps, as shown in the following Equation (21) (Train, 2009).

$$\begin{aligned} &\Gamma \mid \Sigma, \beta_n \\ &\Sigma \mid \beta_n, \Gamma \\ &\beta_n \mid \Gamma, \Sigma \end{aligned} \quad \text{Eq. (21)}$$

Specifically, the parameter Γ that corresponds to vector $\mathbf{z_n}$, which represents the characteristics of individual respondents n, is extracted with given covariance Σ between parameters β_n and individual-level parameters β_n of attributes; Σ is extracted with β_n and Γ given, and β_n is extracted with Γ and Σ given. Thus, taking the two parameters instead of one parameter as conditional in the probability extraction process reflects the hierarchical structure of the parameters (Allenby & Ginter, 1995).

2.2 Alternative Consumer Choice Theory and Model

The majority of previous studies to analyze consumer preferences and demand forecasting use a standard discrete choice model, in which it is assumed that the respondent perceives and processes the level of the attributes presented in the alternative. However, reference dependence is reported to be very important in almost everyday life situations, and its effect is widely found in consumer behavior study (Bell & Bucklin 1999; Laibson & List, 2015). Therefore, questions have been raised about the reliability and validity of consumers' preferences and welfare results derived from the choice model that ignores the reference point effect (Caputo, Lusk, & Nayga, 2018).

Since consumers have bounded rationality, heuristics play an important role in choice experiments as well as in actual decision-making processes (Kjær, Bech, Gyrd-Hansen, & Hart-Hansen, 2006). In this regard, multiple heuristics, including the context effect, illustrate consumers' decision strategies regarding the characteristics and complexity of the choice task, and the reference point effect, called the "relational" heuristic, emphasizes the relative treatment of the levels of the attributes that constitute an alternative. One of the most well-known theories related to this reference point effect is prospect theory (Leong & Hensher, 2012).

Prospect theory deals with choices in the presence of risk, and subsequently, the reference-dependent preference theory has been developed to deal with choices related to certain outcomes in the absence of risk. The basic premise of these theories is that consumers observe choice options in comparison with a reference alternative, such as their current state, for simplicity and ease of decision-making (Tversky & Kahneman, 1991). A significant amount of empirical evidence has shown that consumers' choices are dependent on reference points (Tversky & Kahneman, 1991), and prospect theory and the reference dependence theory can explain consumers' behavior better than the standard utility theory can (Van de Kaa, 2010).

2.2.1 Prospect Theory

Prospect theory deals with choices in situations in which risk exists, which is suitable for consumers' asymmetric preference analysis of overall value or a single attribute. Risk prospect is different from uncertain events. In the case of risk prospect, the probability of outcomes is assumed to be known, while in the case of uncertainty, the probability is assumed to be unknown (Tversky & Fox, 1995). Prospect theory sets the decision-making process as two stages: editing and evaluation (Chorus, 2012). In the editing phase, the consumer constructs the value compared to the reference point into gains or losses. In the evaluation phase, the consumer evaluates the gains and losses by using a decision weight. As a result, the prospect with the highest value is selected (Chorus, 2012). Over the years, researchers have positively confirmed the assumptions of prospect theory in various fields of social science. Thus, prospect theory has become one of the most used theories to analyze consumers' choice behavior in addition to utility theory (Chorus, 2012).

The outcome of the risk prospect is assessed by a value function with the following three essential characteristics (Kahneman & Tversky, 1979). First, the value function is defined as gains and losses in comparison with the reference point, and this characteristic is termed reference dependence. Second, the value function is defined as steeper in the negative domain than in the positive domain, and this characteristic is termed loss aversion. Third, in the value function, the marginal value of gains and losses is defined as reducing with increasing absolute value of the relative level, and this characteristic is termed diminishing sensitivity. The three features of this prospect theory are represented by an asymmetric S-shaped value function, as shown in Figure 4. Here, assuming that a higher value of the attribute level is preferred, in the preferred direction to the right of the reference point, the shape of the curve is concave, and in the non-preferred direction to the left of the reference point, it is convex.

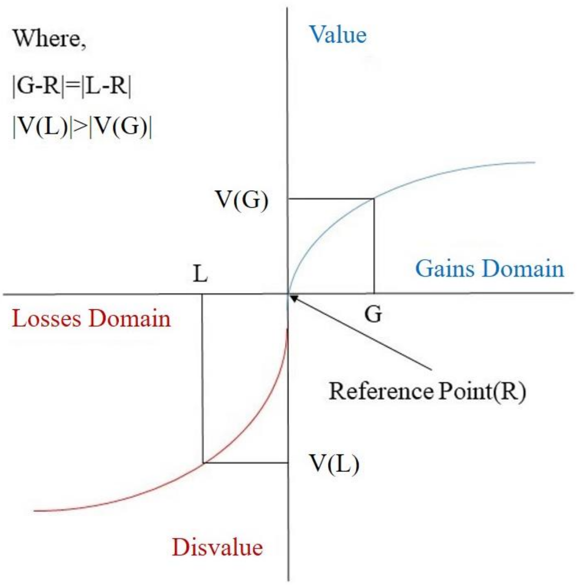

Figure 4. Value Function of Prospect Theory with Three Characteristics

The most important loss aversion effect among the three characteristics of prospect theory is derived from the reference point effect. “Losses loom larger than corresponding gains” (Tversky & Kahneman, 1991, p. 1039), which summarizes the concept of loss aversion, is a popular phrase widely cited (Brenner, Rottenstreich, Sood, & Bilgin, 2007). This tendency, by which consumers strongly prefer loss aversion to gain seeking, is a widespread economic phenomenon (Horowitz & McConnell, 2002). In addition, loss aversion is a universal phenomenon that occurs regardless of experience and culture (Chen, Lakshminarayanan, & Santos, 2006). In psychology, the main driver of this phenomenon is the loss aversion heuristic (Kahneman et al., 1991; Tversky & Kahneman, 1991). Because of the loss aversion tendency, individuals make more efforts to avoid losses than to seek gains (Ayres & Mayer, 2010), and avoid losses through a comparison of alternatives (Chen et al., 2006).

Subsequent studies based on prospect theory focus on the two characteristics of reference dependence and loss aversion among the three characteristics of the value function. First, with regard to reference dependence, value function $V(x)$ is defined as the relative level compared to reference point r, but is not the presented level of the attribute. Second, with regard to loss aversion, the curve of value function $V(x)$ has an inflection point at the reference point; the losses domain $(x < r)$ is steeper than the gains domain $(x \geq r)$.[3] Thus, value function $V(x \mid r)$ is expressed as in the following Equation (22):

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[3]In this case, all respondents prefer a higher level of x; in the opposite case, the losses domain is defined as $(x \geq r)$, and the gains domain is defined as $(x < r)$.

$$V(x \mid r) = \begin{cases} x - r & \text{if } x \geq r \\ \lambda(x - r) & \text{if } x < r \end{cases} \quad \text{Eq. (22)}$$

Here, λ is a loss aversion parameter, which generally is larger than 1 (Tversky & Kahneman, 1991). In other words, when the attribute level is compared with the reference point, the losses have greater influence on consumers' choice than the gains do.

The following Equation (23) shows the standard form of diminishing sensitivity, which means that if attribute level moves away from the reference point, the marginal effect is weakened (Baucells & Sarin, 2013). In other words, researchers should analyze diminishing sensitivity by using a non-linear equation. Thus, unlike Equation (23), it is possible to use a piecewise linear approximation approach, which has the advantage of finding meaningful non-linearities in a small range while keeping the value function linear (Ben-Akiva & Lerman, 1985).

$$\begin{aligned} V(x) &= x^{\beta}, & \text{if } x \geq r \\ V(x) &= -\lambda \mid x \mid^{\beta}, & \text{if } x < r \end{aligned} \quad \text{Eq. (23)}$$

2.2.2 Reference-Dependent Theory

Following prospect theory, the reference-dependent theory was developed; this theory explains consumers' choices in situations in which risk does not exist and analyzes multiple attributes (Tversky & Kahneman, 1991). Choice under no risk means that the consumer knows with certainty the value of the attributes that constitute the alternative

(Chorus, 2012). In the reference-dependent theory, decision-making depends on the reference point that affects the preference form, such as the value function of prospect theory (Tversky & Kahneman, 1991). Subsequently, the reference-dependent theory has been applied to various fields of economics to verify the effect of loss aversion on consumers' choice under no risk (Bateman, Munro, Rhodes, Starmer, & Sugden, 1997; De Borger & Fosgerau, 2008).

The development of the reference-dependent model based on the reference-dependent theory has had a broad impact on consumers' asymmetric preference analysis of multiple attributes (Hardie et al., 1993). In relation to this, it has been found that the reference-dependent evaluation of an attribute can be applied to other attributes of the alternative, besides the price (Simonson & Tversky, 1992). This is because consumers form separated reference points for each attribute of the alternative rather than the reference point related to the overall value of prospect theory (Tversky & Kahneman, 1991). The basic idea of the reference-dependent model is that first, an alternative can be divided into values for each attribute; second, each attribute can be described as a unique feature; and third, each attribute is evaluated based on the reference point (Hardie et al., 1993). In other words, the reference-dependent model is a method in which all alternatives in the multi-attribute space are compared with the reference point of respondents (Tversky & Kahneman, 1991).

The most important consideration in the reference-dependent theory is also loss aversion and asymmetric preference for attributes. The concept of loss aversion for multiple attributes under no risk is derived from the changes of reference points in indifference curves (Kahneman et al., 1991; Tversky & Kahneman, 1991). In various studies using the reference-dependent theory, the existence of loss aversion was established, and loss aversion was found to be dependent on attributes (Bateman et al., 2009; Hess, Rose, & Hensher, 2008; Masiero & Hensher, 2010). Some studies have mentioned that consumers have a greater loss aversion for attributes they perceive as more important (Hankuk & Aggarwal, 2003). However, this is because the relative value of the loss aversion parameter is confused with the relative importance of the attribute (Tversky & Kahneman, 1991). Thus, the parameter estimates derived from the model of the asymmetric form need to be interpreted carefully.

In terms of the loss aversion parameter, which is the weight that captures the degree of loss aversion, Tversky and Kahneman (1991), who proposed the reference-dependent theory, revealed the loss aversion parameter as 2 to 2.5. However, the significance of the loss aversion phenomenon and the value of the loss aversion parameter are different for each study (Briesch, Krishnamurthi, Mazumdar, & Raj, 1997; Kalyanaram & Little 1994; Kim et al., 2016). In other words, although some studies found strong evidence of loss aversion (Kalyanaram & Little 1994), other studies have either found no loss aversion (Briesch et al., 1997) or only partially supported loss aversion (Klapper, Ebling, & Temme 2005). In addition, many studies have found attributes whose loss aversion parameter is not larger than 1 (Hess et al., 2008; Kim et al., 2016), which can be interpreted to mean that the respondent perceives the gain of the attribute to be more important than its loss. Similarly, some empirical evidence supports the reference point effect, which seeks gain over loss at the individual level (Kopalle, Kannan, Boldt, & Arora, 2012; Krishnamurthi, Mazumdar, & Raj, 1992). Therefore, the generalization in existing studies of the concept of loss aversion through the convergence value on the loss aversion parameter is not correct. It is necessary to interpret and apply the results of the loss aversion parameters of each attribute derived from individual empirical studies.

In addition, the concept of loss aversion can explain the endowment effect (Thaler, 1980) and the status quo effect (or status quo bias) (Samuelson & Zeckhauser, 1988). Since the value of the endowment changes when the alternative is integrated into a consumer’s endowment, there is more value in the case of possession than in the case in which there is no possession (Thaler, 1980). Thus, the loss of utility when giving up an alternative is greater than the utility gained when the coresponding alternative is acquired. Next, according to the behavioural decision theory, the status quo effect refers to the consumer’s excessive preference toward maintaining the current state (Kahneman et al., 1991; Samuelson & Zeckhauser, 1988). Accordingly, an economic model that ignores the status quo effect exaggerates the consumer’s response, arriving at extreme and radical conclusions and predicting greater instability than is normally observed (Tversky and Kahneman, 1991).

The most important thing in modeling reference dependence and loss aversion is to establish the reference point of each respondent (Hess, Stathopoulos, & Daly, 2012). In fact, reference dependence and loss aversion should be considered together, because it is difficult to obtain accurate estimates of the loss aversion parameters without careful consideration of reference points. Regarding the setting of reference points, some studies state that respondents' choices are affected by prior experience (Kahneman et al., 1991), beliefs in the future (Kőszegi & Rabin, 2006), and aspirations (Stutzer, 2004). By contrast, the most commonly used reference point is the status quo (Hess et al., 2012). In addition, in Kahneman and Tversky (1979), who proposed prospect theory, and Tversky and Kahneman (1991), who proposed the reference-dependent model, the reference point was set to the status quo. In relation to this, few studies have addressed the emergence process of reference points. Even authors that have suggested the reference-dependent model mentioned that the issue of origin and determinants of reference points is outside the scope of their research (Tversky & Kahneman, 1991).

The case in which the reference point is set as the status quo is described in detail as follows. Even if the reference price is assumed as the status quo, it is influenced by prior experience and indirect knowledge. In this regard, personal experience is a critical factor in establishing a reference price (Briesch et al., 1997), and the application of personal experience requires an assumption that consumers can accurately recall past transaction prices (Briesch et al., 1997). Thus, among the attributes of alternatives, monetary attribute, such as price, is focused when setting a reference point. This is because aside from the price attribute, it is easy for respondents to recognize the level of attributes constituting the status quo, but they do not precisely remember prices they paid in the past (Jensen & Grunert, 2014; Moon, Russell, & Duvvuri, 2006; Urbany & Dickson, 1991). Although, some consumers remember purchase prices well, most surprisingly do not (Krishna, Currim, & Shoemaker, 1991). Therefore, the accuracy and effectiveness of the reference price based on consumers' past purchase prices has been questioned. Because of this challenge, in many studies, respondents were asked about expected price to measure the reference price (Hu, Adamowicz, & Veeman, 2006; Kőszegi & Rabin, 2006; Marzilli Ericson & Fuster, 2011). However, since it is assumed in the method of setting the expected price as the reference point that a consumer will determine the reference point based on the latest purchase price (Kőszegi & Rabin, 2006; Marzilli Ericson & Fuster, 2011), the same criticism applies to setting the recent purchase price as a reference point.

In this regard, there is gaining traction for the argument that the reference point, which is a purely subjective criterion, does not need to depend on objective and accurate memories (Biehal & Chakravarti, 1986). In addition, according to research comparing internal reference point based on past information and internal memory, and external reference point based on external stimuli and economic environment (Briesch et al., 1997), the internal reference point is an important factor in the reference point formation process (Briesch et al., 1997). The result of comparing the model considering the external reference point and the model considering the internal reference point showed a better fit of model reflecting the reference point of the internal memory base (Briesch et al., 1997).

2.2.3 Reference-Dependent Choice Model

The reference-dependent model based on the characteristics of prospect theory, and the discrete choice model based on utility theory are consistent in that multiple attributes affect the utility of a consumer under riskless. Therefore, a reference-dependent choice model has been developed to incorporate the reference-dependent theory into the discrete choice model in order to reflect the reality of behavior in consumers' choice model (De Borger & Fosgerau, 2008; Hess et al., 2008). Prospect theory is intended to explain consumers' abnormal behavior about the complete rationality assumed in utility theory as an alternative consumer theory. However, the purpose of prospect theory is not to examine consumers' optimal behavior, but simply to describe the behavior of consumers. Therefore, to introduce prospect theory and the reference-dependent theory into empirical situations, it is necessary to define the utility structure depending on the reference point. As a result, the value function of prospect theory and the reference-dependent theory is expressed as a utility function.

The key assumption of a reference-dependent choice model that considers the reference-dependent preference in a random utility framework is that the attribute levels of the alternatives are framed as gains and losses compared to the corresponding reference points, which are dependent on the choice context, and each consumer maximizes his or her utility (Laibson & List, 2015; Van de Kaa, 2010). Therefore, the discrete choice model is expressed as a symmetric form, and the reference-dependent choice model is expressed as an asymmetric form. That is, the deterministic term of the discrete choice model is expressed as Equation (24). Furthermore, as Equation (1) was explained in Section 1.2, if each attribute level is compared with the reference point and classified as increasing or decreasing, it can be expressed as Equation (25) (Glenk, 2011;

Hess et al., 2008). In addition, the piecewise linear approximation approach mentioned in Section 2.2.1 is asymmetrical and non-linear, and each attribute level compared with the reference point is divided into two levels in the case of increase and decrease. The asymmetric and non-linear form can be expressed as in Equation (26) (Masiero & Hensher, 2010). However, since the asymmetric and non-linear Equation (26) does not have excellent goodness-of-fit (Masiero, Pan, & Heo, 2016), most studies analyze reference dependence and loss aversion using the model of asymmetric form, as in Equation (25) (Van de Kaa, 2010).

$$V(x)_j = \sum_k \beta_k x_{jk} \quad \text{Eq. (24)}$$

$$V(x|r)_j = \sum_k \beta_k^{+} x_{jk(inc)} + \sum_k \beta_k^{-} x_{jk(dec)} \quad \text{Eq. (25)}$$

$$V(x|r)_j = \sum_k \beta_k^{+} x_{jk(inc+)} + \sum_k \beta_k^{++} x_{jk(inc++)} + \sum_k \beta_k^{-} x_{jk(dec-)} + \sum_k \beta_k^{--} x_{jk(dec--)} \quad \text{Eq. (26)}$$

Here, V_j is the observable value of alternative j, x_{jk} is the level of attribute k that constitutes alternative j, and β_k is the parameter of attribute k. If the level x_{jk} of attribute k is larger than or the same as reference point r_{nk} ($x_{jk} \geq r_{nk}$), the difference is expressed as $x_{jk(inc)}$. By contrast, if the level x_{jk} of attribute k is smaller than the reference point r_{nk} ($x_{jk} < r_{nk}$), the difference is expressed as $x_{jk(dec)}$. Furthermore, $x_{jk(inc)}$ can be devided into $x_{jk(inc+)}$ and $x_{jk(inc++)}$ depending on the increasing degree of difference compared to the reference point, and $x_{jk(dec)}$ can be devided into $x_{jk(dec-)}$ and

$x_{jk(dec--)}$ depending on the decreasing degree of difference compared to the reference point.

However, in Equation (25), $x_{jk(inc)}$ and $x_{jk(dec)}$ consider only the difference between level x_{jk} of attribute k and reference point r_{nk}. In other words, special care must be taken when interpreting the parameter sign, as it does not distinguish between desirable and undesirable attributes (Román & Martín, 2016). Therefore, the asymmetric form of the existing reference-dependent choice model is divided into preference (i.e., desirable or good) and non-preference (i.e., undesirable or hate) domains, so as to express the parameters easily, as in Equation (27) (Kim et al., 2016; Kim et al., 2018). However, as explained in Section 1.2, using Equations (25) and (27) to analyze attributes whose preferred directions of consumers are different is inconsistent with economic concepts and definitions.

$$\begin{aligned} U_{nj} = &\sum \beta^{p}_{nk_{sg}} (x_{jk_{sg}} - r_{nk_{sg}})_{\mathrm{I}(x_{jk_{sg}} \geq r_{nk_{sg}})} + \sum \beta^{np}_{nk_{sg}} | x_{jk_{sg}} - r_{nk_{sg}} |_{\mathrm{I}(x_{jk_{sg}} < r_{nk_{sg}})} \\ &+ \sum \beta^{p}_{nk_{sh}} | x_{jk_{sh}} - r_{nk_{sh}} |_{\mathrm{I}(x_{jk_{sh}} < r_{nk_{sh}})} + \sum \beta^{np}_{nk_{sh}} (x_{jk_{sh}} - r_{nk_{sh}})_{\mathrm{I}(x_{jk_{sh}} \geq r_{nk_{sh}})} + \varepsilon_{nj} \end{aligned} \quad \text{Eq. (27)}$$

Here, $x_{jk_{sg}}$ is the level of attribute k_{sg}, for which the preferred direction of consumers is the same and desirable. Furthermore, $x_{jk_{sh}}$ is the level of attribute k_{sh}, for which the preferred direction of consumers is the same and undesirable. Moreover, $r_{nk_{sg}}$ and $r_{nk_{sh}}$ are reference points of respondent n corresponding to attributes k_{sg} and k_{sh}. In addition, if the difference between the attribute level and the reference point of the attribute is preferred, parameters are expressed as $\beta^{p}_{nk_{sg}}$ or $\beta^{p}_{nk_{sh}}$, and if otherwise, they are expressed as $\beta^{np}_{nk_{sg}}$ or $\beta^{np}_{nk_{sh}}$. The subscript n of the parameters reflects the heterogeneity of the respondents. In other words, it is the form expressed when a mixed logit model is selected among the discrete choice models. As a result, the expected signs of the estimated parameters can be expressed simply and clearly, as in Equations (28) and (29) below, unlike the forms defined in previous studies. Thus, the parameters of the preferred direction have a positive value, as in $\beta^{p}_{nk_{sg}}$ and $\beta^{p}_{nk_{sh}}$, while the parameters of the non-preferred direction have negative values, as in $\beta^{np}_{nk_{sg}}$ and $\beta^{np}_{nk_{sh}}$.

$$\frac{\partial V_j}{\partial x_{jk_{sg}}} > 0 = \begin{cases} \beta^{p}_{nk_{sg}} & if \quad x_{jk_{sg}} \geq r_{nk_{sg}} \\ -\beta^{np}_{nk_{sg}} & if \quad x_{jk_{sg}} < r_{nk_{sg}} \end{cases} \Rightarrow \beta^{p}_{nk_{sg}} > 0 \;\; and \;\; \beta^{np}_{nk_{sg}} < 0 \cdots\cdots\cdots\cdots \text{Eq. (28)}$$

$$\frac{\partial V_j}{\partial x_{jk_{sh}}} < 0 = \begin{cases} \beta^{np}_{nk_{sh}} & if \quad x_{jk_{sh}} \geq r_{nk_{sh}} \\ -\beta^{p}_{nk_{sh}} & if \quad x_{jk_{sh}} < r_{nk_{sh}} \end{cases} \Rightarrow \beta^{np}_{nk_{sh}} < 0 \;\; and \;\; \beta^{p}_{nk_{sh}} > 0 \cdots\cdots\cdots\cdots \text{Eq. (29)}$$

Next, the reference-dependent choice model can capture the asymmetry of MWTA and MWTP, which are discussed as economic phenomena, in addition to capturing the loss aversion parameter of the attributes (Brown, 2005; Courset et al., 1987; Hanemann, 1991; Plott & Zeiler, 2005). The disparity between MWTA and MWTP is commonly observed in both market and non-market goods in hypothetical experiments as well as in real situations (Horowitz & McConnell, 2002). However, Equation (6) confirms, if the loss aversion parameter of the monetary and non-monetary attributes is larger than 1, in the case of a discrete choice model assuming symmetric preference, the MWTA for the non-preferred direction is underestimated and the MWTP for the preferred direction is overestimated. Thus, symmetric preference-based MWTA and MWTP induce biased welfare estimates. In general, empirical studies have shown that MWTA is larger than MWTP is, but there is no consensus on why there is a disparity between the two values (Tunçel & Hammitt, 2014). In this regard, the reference-dependent effect and the loss aversion effect, which are representative heuristic concepts, can explain the disparity between MWTA and MWTP.

Neumann and Böckenholt (2014) conducted a meta-analysis of studies on the asymmetric preference of consumers for multiple attributes using the reference-dependent choice model, as in Equation (20); their key findings are summarized as follows. First, since the reference-dependent variable must have only a positive or negative sign, it is reasonable to assume that the domains of gains and losses have log-normal distributions. Nevertheless, of the 71 studies that considered heterogeneity for the parameters of the domains, only 3 were assumed to have log-normal distributions. Second, the model that considers heterogeneity of preferences for the parameters of gains and losses domains shows smaller loss aversion parameter estimates than the model that does not consider preference heterogeneity. The loss aversion parameter is slightly different depending on the model used, which is about 1.5 on average. Third, as the loss aversion parameter of durable goods is larger than the loss aversion parameter of non-durables, the goods type can be an important factor of asymmetric preference. However, as there is no significant difference in the loss aversion parameters between price and quality attributes, the attribute type does not play an important role in asymmetric preference.

2.3 Reference Points Shifting with Decision Strategies

Studies analyzing consumers' behavior over the past decades demonstrate that consumers' choices can often be influenced by several factors not included in the standard choice model (Mabit, Cherchi, Jensen, & Jordal-Jørgensen, 2015). Among these factors, the important points to be discussed are the reference point effect and context effect (McFadden et al., 1999). Loss aversion, which can be explained by the reference point effect, corresponds to a special case of context effect. Context dependence is recognized as an important heuristic in behavioral decision theory (Bettman, Johnson, Luce, & Payne, 1993; Dhar, 1997; Swait & Adamowicz, 2001; Tversky & Shafir 1992), and it is also acknowledged by some neoclassical economists (De Palma, Myers, & Papageorgiou, 1994; DeShazo & Fermo, 2002; Heiner, 1983). However, although consumers' reference points are likely to be shifted or modified by a choice context (Ariely et al., 2003), the existing reference-dependent choice model adopts a fixed reference point framework (Tversky & Kahneman, 1991).

2.3.1 Heuristics in the Decision Process

The early approach of cognitive psychology studies focused primarily on showing that consumers' choice behavior does not necessarily correspond to the complete rationality of the basic assumption of neoclassical economic models. Since then, many efforts have been made to suggest an alternative approach of neoclassical consumer theory and standard economic models by theorizing and modeling the decision process allowing elements of cognitive psychology in consumer research and behavioral economics. In other words, new methods including one or more “human” aspects of choice behavior to enrich or substitute the approach of the standard economic model have emerged. The “human” aspect of the choice behavior is based on the bounded rationality of consumers. Thus, while neoclassical economists analyze consumer choice based on a utility maximization model, behavioral economists mainly discuss the behavior of consumers induced by heuristics, and the importance of including heuristics in standard economic models has been emphasized in analyzing consumer choice (McFadden, 2001).

Consumers have frequent anomalies in their behavior that are not entirely rational, which is conter to the basic assumption of the standard economic model. For example, consumers’ preferences and judgments can be changed and depend on choice context (Ariely et al. 2003; Huber et al., 1982; Tversky & Simonson 1993). In addition, consumers tend to make choices using various decision strategies, as they have limited rationality (Manzini & Mariotti 2007; Tversky & Kahneman 1974). Therefore, the presence of too many attributes or non-critical attributes in a decision process leads to heuristic-dependent choices, along with inconsistent and probabilistic choice (Bennett & Blamey, 2001).

The heuristics of human behavior include various rules besides the reference point effect discussed in Section 2.2. This section focuses on the context effect. The context effect is one of the important heuristic rules; it is a heuristic that occurs when decision-makers, such as consumers, encounter choice situations (Leong & Hensher, 2012).

Consumers' main decision strategies for explaining the context effect can be divided into satisficing (Simon, 1955), lexicography (Tversky, 1969), elimination-by-aspects (EBA) (Tversky, 1972), and the majority of confirming dimensions (Russo & Dosher, 1983). The precondition for such decision strategies is that the choice of consumers is primarily influenced by the order of importance of the attributes that constitute the alternative (Bettman & Park, 1980). The main concepts of decision strategies summarized by Leong and Hensher (2012) are shown in Table 1.

In general, such decision strategies are known to be used more frequently as the choice task becomes more complicated (Payne, Bettman, & Johnson, 1993; Tversky, 1972). The complexity of the task is determined by the choice context, such as the number of alternatives in the choice set, the number of attributes of each alternative, and correlation of the level of attributes between alternative (Leong & Hensher, 2012). In other words, the variety of the attributes may lead respondents to make inconsistent choices and to make choices around the important attributes, which is referred to as the context effect (Bennett & Blamey, 2001).

It is assumed in the standard choice model that respondents' choices are made through trade-offs of all attributes (Kaye-Blake, Abell, & Zellman, 2009; McFadden & Train, 2000). However, if this assumption is not consistent with the actual decision-making process, inaccurate estimates of welfare are derived. For this reason, behavioral economists have suggested that consumers deal with a complicated choice situation by adopting a non-compensatory decision rule and simplified decision strategies, and have presented models considering such heuristics (Hensher, Rose, & Bertoia, 2007; Simonson & Tversky 1992; Swait & Adamowicz, 2001). To integrate a non-compensatory decision rule into the standard economic model based on the utility maximization framework, decision strategies and constraints should be added to the model as well as the deterministic term of utility consisting of attributes (Swait, 2001).

Table 1. Main Decision Strategies and Concepts Explaining Context Effect

Decision Strategy	Main Concept
Satisficing	Respondents define cutoffs for attributes in advance and choose the first alternative whose attribute levels all satisfy the cutoff criterion (Leong & Hensher, 2012). When there is no alternative meeting the cutoff criterion, the cutoff is relaxed, and the process is repeated, or probabilistic choices are made (Leong & Hensher, 2012).
Lexicography	Respondents evaluate alternatives based on the attribute that they consider most important, and if an alternative is found to be superior to the others based on the attribute, the respondent chooses it (Leong & Hensher, 2012). If the most important attribute has the same or similar levels, the alternatives are compared for the next most important attribute (Leong & Hensher, 2012).
EBA	Respondents first identify the cutoff threshold for the most important attribute (Leong & Hensher, 2012). The alternatives that do not satisfy the criterion are eliminated (Leong & Hensher, 2012). This process is repeated for the next most important attribute, until there is only one alternative left (Leong & Hensher, 2012).
Majority of confirming dimensions	Respondents compare the first two alternatives and preserve the alternative with the higher number of superior attribute levels (Leong & Hensher, 2012). Preserved alternatives are compared with the next, and the process is repeated until all the alternatives have been considered (Leong & Hensher, 2012). Finally, respondents choose the alternative with the highest number of superior attribute levels (Leong & Hensher, 2012).

Cutoffs, mostly discussed in the decision strategy explaining the context effect as a key heuristic, are explained as follows. Consumers often consider cutoffs as a tool to simplify a complicated decision-making process (Huber & Klein, 1991; Swait, 2001). It has been found that the higher is the number of alternatives, the higher is the tendency of consumers to use a cutoff threshold (Klein & Bither, 1987). In addition, the selection of criteria for the cutoff is influenced by the importance of an attribute (Grether & Wilde, 1984). To reflect the cutoff criteria in the standard choice model, a two-stage decision-making process should be in place (Robert & Lattin, 1991). In the first stage, the consumer screens the alternatives and eliminates those not satisfying the criteria set for the cutoff. In the second stage, the consumer is supposed to choose an alternative out of the remaining ones using a compensatory decision rule (Robert & Lattin, 1991). Cutoffs can be divided into hard and soft (Swait, 2001). A hard cutoff is an attribute level that must be reached or must not be violated to allow a valid choice (Swait, 2001). Thus, constraints should be put in place to prevent respondents from choosing an alternative that violates the stated cutoff criterion to incorporate hard cutoffs in the model (Bush, Colombo, & Hanley, 2009). However, it has been revealed that respondents often violate their cutoff criteria (Huber & Klein, 1991; Swait, 2001). It is understandable that they may violate the criteria for a single attribute because they make an overall evaluation of the attributes included in the alternative (Swait, 2001).

2.3.2 Reference Points Shifting

As the importance of the reference point effect is emphasized in analyzing consumer preference and behavior, recently, many studies have used the reference-dependent choice model. As emphasized repeatedly, in the existing reference-dependent choice model, a fixed reference point framework is assumed. Although some studies consider a shifting reference point, they mostly focus on dynamic analysis by explaining that reference points can change over time (Baucells, Weber, & Welfens, 2011). However, in a cross-sectional situation, changes in reference points are induced by diverse causes, such as choice context and the importance of attributes (Ariely et al., 2003; Loomes et al., 2009). In this regard, it has been found that the cutoff, a stronger criterion than the reference point, is also not fixed, as consumers adjust the cutoff criterion during the decision-making process (Huber & Klein, 1991; Klein & Bither, 1987; Swait, 2001).

Unfortunately, there has been little research dedicated to the analysis of decision-making change by reference points shifting. One notable exception is a comparative analysis of decision-making differences using initial and shifted reference points (Masiero & Hensher, 2011). Masiero and Hensher (2011) conducted a choice experiment focusing on individual reactions to a negative change in the reference points. The initial reference points of all respondents were updated with the same change to analyze the effect of reference points shifting. In particular, shifted reference points were not defined by the respondent but were formulated by the researchers to reflect directly in the choice task. The results show that loss aversion parameter for some attributes increase on average to prevent the additional loss around negative reference points shifting, and decrease for others.

In addition, some studies on the choice process of the consumer over time have discussed the updating of reference points. This is because consumers observe various prices and consider several reference prices to make a choice during the decisions-making process for purchases over a period of time (Bell & Lattin, 2000). In particular, Kahneman and Tversky (1979) mentioned that consumers may assess gains and losses from psychological reference points that shift over time. Against this backdrop, some researchers have a combination of initial purchase price and latest purchase price as a reference price (Weber & Camerer, 1998). Baucells, Weber, and Welfens (2011) conducted experiments and insisted that a reference price is not formed repeatedly, because the most appropriate reference price for the respondent is the combination of the first and last prices in a time series. By contrast, there has been some empirical analysis of the reference price adjusted over time (Meulenberg & Pennings, 2002).

With the emergence of prospect theory, the shifting of reference point has been emphasized; however, it is still assumed in the existing literature that the reference points are fixed (Jin & Zhou, 2008; Kahneman & Tversky, 1979). In other words, little is known about the shifting rule for formulating and updating reference points in consumers' choice process (Mattos & Zinn, 2016; Shi, Cui, Yao, & Li, 2015). It has been found that under the assumption of the reference-dependence theory, reference points shifting influences the preference structure of consumers (Masiero & Hensher, 2011). In particular, reference points, which effectively explain the consumer behavior, are likely to shift in the choice context (Ariely et al., 2003; Loomes et al., 2009). In addition, although the ratio of MWTA to MWTP may be overestimated when reference points shifting is ignored (Masiero & Hensher, 2011), no suggestions for the reference points shifting rule have been made in the research using the existing reference-dependent choice model.

In summary, it is necessary to abundantly reflect the reality of behavior in the standard economic model to undertake more accurate analysis of consumer preference and behavior and to obtain unbiased welfare estimates (McFadden, 2001). At the same time, models that consider preference heterogeneity and include weighted reference points are being recommended (Van Oest, 2013). However, there has been little empirical exploration of the shifting of respondents' reference points. In this regard, a problem may arise in relation to dummy variables when establishing the reference points shifting rule. This is because dummy variables do not have a value of 0 or 1, unlike linear variables. However, according to the reference point adaptation model, consumers cannot completely adapt to gains or losses and it does not need to be all (1) or nothing (0) when it comes to recognizing ownership (Strahilevitz & Loewenstein, 1998). Specifically, adaptation is represented by the shifting of a reference point in the direction of endowment (Strahilevitz & Loewenstein, 1998). In short, the reference point of each respondent, r_{nk}, can be placed between 0 and 1.

2.4 Research Motivation

The RUT has been positioned as a dominant behavioral decision theory in economics and related studies. Studies using the discrete choice model based on the RUT analyze the choice and preferences of consumers under the assumption that individuals follow a perfect compensatory decision rule for all attributes in the choice set (Leong & Hensher, 2012; McFadden & Train, 2000). This discrete choice model is acknowledged as useful and effective in analyzing consumers' preferences. However, the explanation provided by the standard choice model has been limited with regard to heuristics, the framing effect, and systematic violation behavior owing to the assumption of rational behavior. In addition, the discrete choice model is symmetrical, and estimates the same absolute values for MWTA and MWTP (McFadden, 1973; Train, 2009). In this case, the disparity between MWTA and MWTP can be ignored. This consequently causes the underestimation of MWTA and overestimation of MWTP in terms of social and economic welfare assessment (Brown, 2005; Coursey et al., 1987; Hanemann, 1991; Plott & Zeiler, 2005). Against this backdrop, a number of questions are raised about the validity of neoclassical customer behavioral theory, hence, it is important to incorporate psychological factors, such as heuristics, into the neoclassical economic model in order to reflect consumers' behavior more precisely (Bateman et al., 2009; McFadden, 2001).

In economics research, consumer studies and behavioral economics have developed choice models by integrating heuristics based on the bounded rationality of consumers, advocated by cognitive psychology, into the standard economic model (Kahneman, 2003;

Starmer, 2000;). In particular, the reference-dependent model considering the reference point effect, known to have an important effect on consumers' choice among heuristics (McFadden et al., 1999), has emerged and been applied to economics and other related areas (Tversky & Kahneman, 1991). In other words, to capture the elements dominating the preferences and decisions of individuals, the components of the reference-dependent theory are incorporated into the standard economic model for modeling realistic decision-making processes and the reference-dependent choice model is a result of asymmetric modeling of consumers' preference in an approach to reflect real-life (De Borger & Fosgerau, 2008; Feo-Valero, Arencibia, & Román, 2016).

However, as explained in detail in Section 1.2, the analysis of asymmetric preferences for attributes, for which the preferred direction of consumers is different, using the existing reference-dependent choice model, has limitations, as it contradicts the economic definition of the loss aversion parameter, MWTA, and MWTP (Hensher et al., 2005; Kahneman & Tversky, 1979; Shogren et al., 1994). Therefore, when using the model, asymmetric preferences can be analyzed only for some attributes that are presumed to have the same preference direction among consumers (Kim et al., 2016; Kim et al., 2018). Therefore, the existing asymmetric reference-dependent choice model has been used mostly in transportation, where the attributes that are assumed to have the same preference direction among consumers, such as time and cost, are considered important (Hess et al., 2008; Masiero & Hensher, 2010). Therefore, this study proposes a reference-dependent choice model based on consistency, which can capture reference-dependent and asymmetric preferences for all attributes, including those with different preference directions among consumers.

Moreover, consumers' preferences and behavior are greatly influenced by the context effect as well as the reference point effect (Leong & Hensher, 2012; McFadden et al., 1999). In particular, the existing reference-dependent choice model is limited, because it is based on the fixed reference point framework (Tversky & Kahneman, 1991), even though the reference point of subjective concepts is likely to shift from the choice context perspective (Ariely et al., 2003; Loomes et al., 2009). In summary, there is no discrete choice model that integrates the reference point effect and context effect even though they are regarded the most important among heuristics. Therefore, this study proposes a reference points shifting rule based on the major decision strategy theories (which explain the context effect) and the loss aversion effect (which can be explained by the reference point effect and the context effect). In addition, this study proposes an advanced reference-dependent choice model that integrates the reference points shifting rule into the reference-dependent choice model.

Chapter 3. Methodology

This chapter introduces a reference-dependent choice model based on consistency, which integrates the consumer's reference-dependent and context-dependent behavior. First, Section 3.1 presents a general framework of the research methodology. Section 3.2 proposes a reference-dependent choice model based on consistency, which integrates the reference point and preference heterogeneity, enabling analysis of the consumer's asymmetric preferences for all attributes regardless of the preferred directions. Section 3.3 proposes reference points shifting rule based on loss aversion and decision strategy theories, and the rule is integrated into the reference-dependent choice model presented in Section 3.2 to propose an advanced reference-dependent choice model.

3.1 Methodological Framework

This study derives consumers' asymmetric preferences based on consistency and proposes a new asymmetric reference-dependent choice model integrating heuristics. The overall methodological framework is shown in Figure 5. First, as described in Section 1.2, the preference directions of each attribute should be identified to analyze the consumer's reference-dependent preferences, which are consistent with economic definitions for the attributes for which the preferred direction is different. First, attributes with the same preference direction and those with different preference directions should be identified in advance using the Bayesian mixed logit model, and individual-level parameters for the attributes for which the preferred direction is different, derived through Bayes' theorem, should be incorporated into the reference-dependent choice model. Next, the individual-level parameters for the attributes for which the preferred direction is different and the differences between the attribute levels of the alternatives and corresponding reference points are used to build a model dividing the attributes into preference and non-preference domains. When the attributes are assumed to have the same preference direction, they are divided into preference and non-preference domains only using the difference between the attribute levels of the alternatives and corresponding reference points, as in the existing reference-dependent choice model. With this method, the reference-dependent choice model with consistency is constructed to analyze consumers' asymmetric preferences for attributes with the same and different preference directions.

Next, the importance of loss aversion is derived by using the parameter for non-preference domain and the difference between the minimum level of the attribute composing the alternative and the reference point. Then the individual-level importance of loss aversion for each attribute is ordered. In the order of attributes with high importance of loss aversion, when the attribute level of each alternative is preferred to the reference point of the consumer, the reference points shifting rule is set to shift the reference point of the attributes with relatively low importance of loss aversion. If the number of attributes considering the reference points shifting rule is not the same as that of the attributes of the alternative, the relative importance of the attributes is reflected as a weighted value. Finally, the reference point effect and context effect are integrated into the newly constructed advanced reference-dependent choice model by including the reference points shifting rule in the reference-dependent choice model.

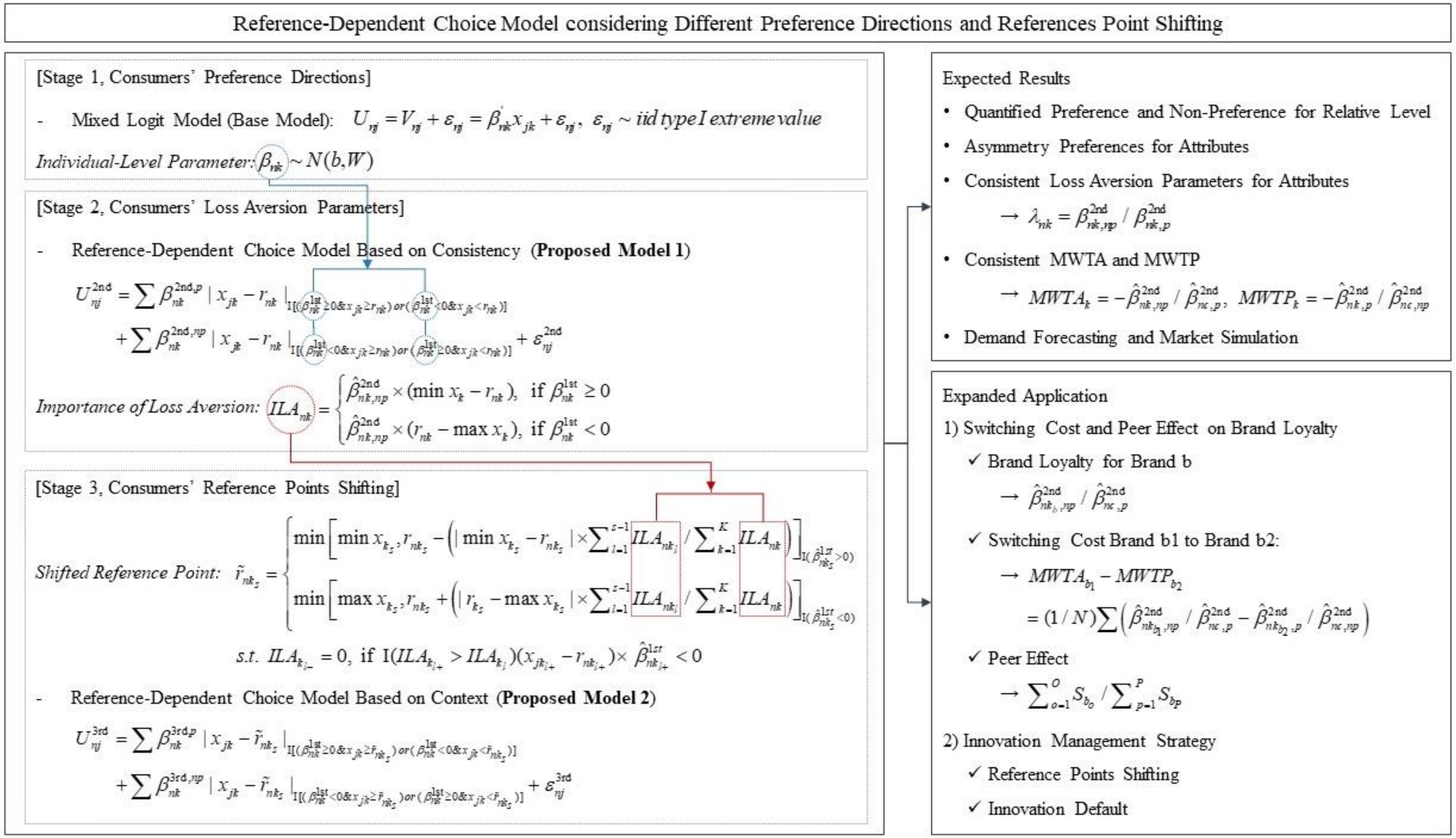

Figure 5. Research Methodology of This Study

3.2 Reference-Dependent Choice Model Based on Consistency

For analyzing asymmetric preferences for attributes for which the preferred direction is different, it is necessary to build a reference-dependent choice model based on consistency. In other words, the relative levels of attributes for which the preferred directions are different cannot be divided by the reference point into gains and losses, and the relative levels should be divided into preference and non-preference domains using the reference point and preference heterogeneity. To do this, this study divides the modeling process into two stages. Then, I propose a reference-dependent choice model based on consistency, which can analyze reference-dependent preferences for all attributes by integrating the existing reference-dependent choice model suitable for the analysis of asymmetric preferences for attributes for which the preferred direction is the same.

3.2.1 Overview of the Model

A two-stage process is needed to develop and propose a reference-dependent choice model based on consistency for analyzing asymmetric preferences for attributes for which the preferred direction is different among respondents. In the first stage, preferred directions for each attribute in the alternatives are analyzed using the mixed logit model, among discrete choice models, which can capture preferences at the individual level. The individual-level parameters, derived from the analysis of the first stage using Bayes' theorem, are one of the standards to divide the preferences for attributes of each respondent into preference and non-preference domains. Next, in the second stage, the reference points of each respondent are combined with the individual-level parameters from stage 1 to divide each attribute level into domains of preference and non-preference, not those of gains and losses, and each consumer's asymmetric preferences for attributes for which the preferred direction is different are analyzed.

The division for relative levels of the attributes for which the preferred direction is different can be explained more easily through the discrete choice experiment as follows. A respondent's parameter sign for a specific attribute is (+) at the outcome of the first stage, which means that the respondent prefers the attribute as its level increases. The reference point for the attribute is 4.5. Furthermore, the levels of the attribute in each alternative of a specific choice set in the discrete choice experiment are assumed set, as Part A in Figure 6. Here, the relative levels of the attribute, or the difference between the levels of the attribute and the reference point in the three alternatives, are represented as Part B. Since, respondents have greater preference as the level of the attribute increases, the domains of preference and non-preference for the attribute are represented as Part C.

Part A.

Alternative	Type A	Type B	Type C	Reference Point
Attribute Level	5.5	3.5	4.8	4.5

Part B.

Alternative	Type A	Type B	Type C
Relative Level	1.0	-1.0	0.3

Part C.

Preference Domain	Alternative	Type A	Type B	Type C
	Relative Level	1.0	0	0.3
Non-Preference Domain	Alternative	Type A	Type B	Type C
	Relative Level	0	-1.0	0

Figure 6. An Example of Dividing Preference and Non-Preference Domains

3.2.2 Model Specification

In other to consider consistent reference-dependent preferences as described in Section 1.2, preference heterogeneity of consumers on specific attributes should be captured, as well as the relative attribute levels, which are the difference between the attribute level and the corresponding reference point. In this case, Equation (25), which simply expresses the exsting reference-dependent choice model, is expressed as the following Equation (30). Thus, the relative levels of attributes are not simply divided into an increase and a descrease as in Equation (25), but are divided into preference domain $x_{jk(pre)}$ and non-preference domain $x_{jk(non-pre)}$, and the parameters for the domains are β_{nk}^{pre} and $\beta_{nk}^{non-pre}$.

$$V(x \mid r_n, \hat{\beta}_n)_j = \sum_k \beta_{nk}^{pre} x_{jk(pre)} + \sum_k \beta_{nk}^{non-pre} x_{jk(non\text{-}pre)} \quad \cdots\cdots \text{Eq. (30)}$$

In this study, the mixed logit model with random parameters is used to capture the consumers' preferred directions for the attributes of the alternative and each random parameter is set as having a normal distribution to consider the differences in a preferred direction. When using the mixed logit model, individual-level parameter β_{nk} can be derived with Bayes' theorem (Hensher & Greene, 2003). In particular, since consumers' reference points are not identical and each consumer has a different reference point, behavioral theory, such as reference-dependence theory, has to be dealt with on a strictly individual level. Therefore, to maintain theorical consistency, the framework of the mixed logit model considering respondents' heterogeneity is more suitable than other discrete choice models.

By using parameter β_{nk} of individual respondent n for the attributes for which the preferred direction is different, and the difference between level x_{jk} of attribute k of alternative j and the reference point r_{nk} for attribute k of respondent n, relative attribute levels can be divided into preference and non-preference domains, as in Equation (31). If the difference between level x_{jk} of attribute k of alternative j and the reference point r_{nk} has the same sign as β_{nk}, this means that the respondent prefers the relative attribute level of the alternative and otherwise, the respondent does not prefer the relative attribute level.

$$\begin{aligned}&\text{Preference, if } (\beta_{nk}^{\text{1st}} \geq 0 \,\&\, x_{jk} \geq r_{nk}) \text{ or } (\beta_{nk}^{\text{1st}} < 0 \,\&\, x_{jk} < r_{nk})\\&\text{Non-Preference, if } (\beta_{nk}^{\text{1st}} < 0 \,\&\, x_{jk} \geq r_{nk}) \text{ or } (\beta_{nk}^{\text{1st}} \geq 0 \,\&\, x_{jk} < r_{nk})\end{aligned} \quad \cdots\cdots\cdots\cdots \text{Eq. (31)}$$

The influence of relative attribute levels divided into preference domain and non-preference domain on the utility of respondent n can be modeled as Equation (32). The reference point in the equation is a subjective criterion and does not need to depend on objective and accurate memory (Biehal & Chakravarti, 1986). In addition, because each respondent has one reference point for each attribute of an alternative (Tversky & Kahneman, 1991), reference point r_{nk} for attribute k is samely applied to the corresponding attributes of all alternatives.

$$\begin{aligned}U_{nj}^{\text{2nd}} &= \sum \beta_{nk,p}^{\text{2nd}} \,|\, x_{jk} - r_{nk} \,|_{\mathrm{I}[(\beta_{nk}^{\text{1st}} \geq 0 \& x_{jk} \geq r_{nk}) \text{or} (\beta_{nk}^{\text{1st}} < 0 \& x_{jk} < r_{nk})]}\\&+ \sum \beta_{nk,np}^{\text{2nd}} \,|\, x_{jk} - r_{nk} \,|_{\mathrm{I}[(\beta_{nk}^{\text{1st}} < 0 \& x_{jk} \geq r_{nk}) \text{or} (\beta_{nk}^{\text{1st}} \geq 0 \& x_{jk} < r_{nk})]} + \varepsilon_{nj}^{\text{2nd}}\end{aligned} \quad \cdots\cdots\cdots\cdots \text{Eq. (32)}$$

It is found that parameter $\beta_{nk}^{\text{2nd},np}$ for non-preference domain is, in general, larger than parameter $\beta_{nk}^{\text{2nd},p}$ for preference domain, and the ratio of the two parameters is referred to as the loss aversion parameter. Accordingly, parameter $\beta_{nk}^{\text{2nd},np}$ can be represented as Equation (33). The results from the equation are consistent with economic definitions.

$$\beta_{nk,np}^{\text{2nd}} / \beta_{nk,p}^{\text{2nd}} = \lambda_{nk} \rightarrow \beta_{nk,np}^{\text{2nd}} = \beta_{nk,p}^{\text{2nd}} \lambda_{nk} \quad \cdots\cdots\cdots\cdots \text{Eq. (33)}$$

The following hypothesis is set to validate the respondents' asymmetric preferences. Equation (34) shows the null hypothesis set as "the respondents' preference for attribute k is symmetrical" and the alternative hypothesis set as "the respondents' preference for attribute k is asymmetrical."

$$\begin{aligned} H_0 &= \hat{\beta}^{\text{2nd}}_{k,np} / \hat{\beta}^{\text{2nd}}_{k,p} = \hat{\beta}^{\text{2nd}}_{n,p}\hat{\lambda}_k / \hat{\beta}^{\text{2nd}}_{k,p} = \hat{\lambda}_k = 1 \\ H_1 &= \hat{\beta}^{\text{2nd}}_{k,np} / \hat{\beta}^{\text{2nd}}_{k,p} = \hat{\beta}^{\text{2nd}}_{n,p}\hat{\lambda}_k / \hat{\beta}^{\text{2nd}}_{k,p} = \hat{\lambda}_k \neq 1 \end{aligned} \qquad \text{Eq. (34)}$$

To evaluate the significance of the asymmetric preferences for the attribute, or the difference between the parameters for the preference domain and non-preference domain, a t-test (Kim et al., 2016) or an asymptotic t-ratio test can be conducted (Hess et al., 2008; Román & Martín, 2016).

Integration of the existing reference-dependent choice model, Equation (27), with Equation (34), which can consider asymmetric preferences for the attributes for which the preferred direction is different, results in the reference-dependent choice model based on consistency taking asymmetric preferences for all attributes, as represented by Equation (35).

$$
\begin{aligned}
U_{nj}^{\text{2nd}} = & \sum \beta_{nk_{sg},p}^{\text{2nd}} (x_{jk_{sg}} - r_{nk_{sg}})_{\text{I}(x_{jk_{sg}} \geq r_{nk_{sg}})} + \sum \beta_{nk_{sg},np}^{\text{2nd}} | x_{jk_{sg}} - r_{nk_{sg}} |_{\text{I}(x_{jk_{sg}} < r_{nk_{sg}})} \\
& + \sum \beta_{nk_{sh},p}^{\text{2nd}} | x_{jk_{sh}} - r_{nk_{sh}} |_{\text{I}(x_{jk_{sh}} < r_{nk_{sh}})} + \sum \beta_{nk_{sh},np}^{\text{2nd}} (x_{jk_{sh}} - r_{nk_{sh}})_{\text{I}(x_{jk_{sh}} \geq r_{nk_{sh}})} \\
& + \sum \beta_{nk,p}^{\text{2nd}} | x_{jk} - r_{nk} |_{\text{I}[(\beta_{nk}^{\text{1st}} \geq 0 \& x_{jk} \geq r_{nk}) \text{or} (\beta_{nk}^{\text{1st}} < 0 \& x_{jk} < r_{nk})]} \\
& + \sum \beta_{nk,np}^{\text{2nd}} | x_{jk} - r_{nk} |_{\text{I}[(\beta_{nk}^{\text{1st}} < 0 \& x_{jk} \geq r_{nk}) \text{or} (\beta_{nk}^{\text{1st}} \geq 0 \& x_{jk} < r_{nk})]} + \varepsilon_{nj}^{\text{2nd}}
\end{aligned}
\quad \cdots\cdots \text{Eq. (35)}
$$

It seems reasonable to assume that the attributes considering the reference point effect have a log-normal distribution, because the relative levels for the attributes should have only (+) or (-) signs. In this regard, there are arguments that the model can be improved if parameters are assumed to have a log-normal distribution, instead of a normal distribution, if the sign of the parameters is predictable (Train & Sonnier 2005). However, as mentioned when discussing the mixed logit model in Section 2.1, if it is assumed that parameters have a log-normal distribution, there is a possibility of deriving unrealistic variance measures owing to the fat tails characteristic of log-normal distribution (Patil et al., 2011). Therefore, in most studies using the existing reference-dependent choice model, parameters are set as having a normal distribution during the process reflecting consumers' preference heterogeneity (Neumann & Böckenholt, 2014). In summary, it seems appropriate to examine the propriety of the estimation result under the assumption that parameters for the preference and non-preference domains have a log-normal distribution, which then should determine whether the parameters need to set with a normal distribution.

Asymmetric MWTA and MWTP can be derived as in Equation (36) based on the estimation result from Equation (35), the model proposed by this study. The reference-dependent choice model based on consistency is advantageous, because it can derive MWTA and MWTP consistent with economic definitions, as in the case of the loss aversion parameters. Based on the defenitions of MWTA and MWTP, although preferences for attributes other than cost, such as quality, are symmetrical, MWTA and MWTP can be asymmetrical owing to the asymmetric preferences of currency attributes, such as cost. The same method used to test asymmetric preferences for attributes can be applied to test the statistical significance of the difference between MWTA and MWTP.

$$MWTA_k = -\hat{\beta}^{2nd}_{nk,np} / \hat{\beta}^{2nd}_{nc,p}, \; MWTP_k = -\hat{\beta}^{2nd}_{nk,p} / \hat{\beta}^{2nd}_{nc,np} \quad \text{Eq. (36)}$$

Furthermore, when a reference point effect influences the choice of a consumer, a model that allows trade-offs of preference and non-preference domains of each attribute, should provide a better model fit (Hardie et al., 1993). Since the reference-dependent choice model requires more numbers of parameters than the standard discrete choice model does, the models cannot be compared for goodness-of-fit simply by comparing log-likelihood values. When the number of parameters is different, Akaike information criterion (AIC) (Akaike, 1998) or Bayesian information criterion (BIC) (Schwarz, 1978) statistics are mostly used for more accurate comparison of the model fit. The statistics can reflect the penalty term for the number of parameters included in the model, enabling a less biased evaluation of the model fit. In addition, the BIC statistic has a stronger penalty for the additional number of parameters than the AIC does; the model with the lower AIC or BIC statistic can be considered to have a better model fit.

3.3 Reference-Dependent Model Choice Based on Context

Although the reference point, which explains the consumers' behavior effectively, is likely to be shifted in the choice context, there has been no effort to develop a method on the shifting of reference points of respondents in studies using the reference-dependent choice model. Therefore, this study develops an advanced reference-dependent choice model reflecting the reality of consumer behavior. It does so by proposing reference points shifting rules based on decision strategy theories about the context effect as well as the concept of loss aversion and by integrating them into the reference-dependent choice model based on consistency in Section 3.2.

3.3.1 Overview of the Model

The reference point is likely to shift in the choice context (Ariely et al., 2003; Loomes et al., 2009). Nevertheless, there has been no methodological development and empirical exploration about reference points shifting; however, a fixed reference point framework is used in previous studies related to the existing reference-dependent choice model (Stathopoulos & Hess, 2012; Tversky & Kahneman, 1991). The shifting of reference points is not defined by the respondent but can be formulated by the researcher to reflect directly in the choice model (Swait, 2001). To establish the reference points shifting rule, the loss aversion effect explained by the reference point and context effect should be considered. To do this, this study considers that consumers make great efforts to avoid losses and that the importance of loss aversion for attributes is different. At the same time, it should be considered that the consumer's choice is influenced by the order of the relative importance of loss aversion for attributes of alternatives, considering a prerequisite of decision strategies explaining context effect.

Specifically, this study proposes the reference points shifting rule, by which the reference points of the attributes with relatively low importance of loss aversion shift when the level of attribute with relatively high importance of loss aversion is preferred to the reference point. Accordingly, a key factor in reference points shifting is the importance of loss aversion for each attribute. The reference points shifting rule can be explained through the discrete choice experiment, as shown in Figure 7. For better understanding, it is assumed that consumers' preferred direction is the same and that the preference for the attribute level is in order of H (High), M (Medium), and L (Low). As Figure 7 shows, among the six attributes, attribute B has the highest importance of loss aversion. Furthermore, alternative A has a better level than the reference point for attribute B does. Because the respondent can avoid loss for attribute B in evaluating type A, there is a motive to shift the reference points for other attributes. In this case, the reference point for attribute E, with the second highest importance of loss aversion, shifts slightly, but the reference point for attribute D, sixth in order of importance of loss aversion, shifts much more. The attribute with the fifth highest loss importance of loss aversion has a reference point at the same level as the lowest attribute level. This is the result of the constraints set to reflect reality so that a new reference point for each attribute cannot shift below the most inferior level of that attribute.

Attributes	Type A	Type B	Type C	Degree of Loss Aversion (Order)	Reference Point (RP)	Shifting for Type A
Attribute A	Level L	Level M	Level H	0.1(6)	H	New RP<<<H
Attribute B	Level H	Level L	Level M	0.9(1)	M<RP<H	No Change
Attribute C	Level M	Level H	Level L	0.5(3)	M	New RP<<H
Attribute D	Level L	Level M	Level H	0.3(4)	M	L<New RP<<M
Attribute E	Level H	Level L	Level M	0.7(2)	H	New RP<H
Attribute F	Level L	Level H	Level M	0.2(5)	L	New RP=L

Figure 7. An Example of a Reference Points Shifting Rule in a Discrete Choice Experiment

3.3.2 Model Specification

In this study, the reference points shifting rule is set based on decision strategy theories, which explain the context effect, and loss aversion, which can be explained by the reference point effect. With regard to loss aversion, the consumer's tendency to prefer avoiding losses than seeking gains is observed in all economic phenomena (Horowitz & McConnell, 2002). In addition, consumers avoid losses through comparison of alternatives (Chen et al., 2006). Therefore, the importance of loss aversion ILA_{nk} of respondent n for attribute k should be derived first. To do this, the importance of loss aversion is calculated by multiplying the parameter for the non-preference domain by the difference between the lowest level of attribute in the discrete choice experiment and the corresponding reference point (Dickerson, 1987), similar to the process of deriving the part-worth by multiplying the parameter for attribute by the difference between the minimum and maximum levels of the attribute in the discrete choice experiment (Kim, Park, Lee, & Lee, 2006).

Specifically, the process of calculating the importance of loss aversion, ILA_{nk}, is divided into the following two cases, represented as Equation (37). First, when respondent n prefers an increase in the level of attribute k $(\beta_{nk}^{1st} \geq 0)$, ILA_{nk} can be calculated by multiplying the value, which is obtained by subtracting the respondent's reference point for attribute k from the minimum level of attribute k $(\min x_k - r_{nk})$, by the parameter for the non-preference domain of respondent n for attribute k, $\hat{\beta}_{nk,np}^{2nd}$. Second, when respondent n prefers a decrease in the level of attribute k $(\beta_{nk}^{1st} < 0)$, ILA_{nk} can be calculated by multiplying the value, which is obtained by subtracting the maximum level of attribute k from the respondent's reference point for attribute k $(r_k - \max x_{nk})$, by the parameter for the non-preference domain of respondent n for attribute k, $\hat{\beta}_{nk,np}^{2nd}$.

$$ILA_{nk} = \begin{cases} \hat{\beta}_{nk,np}^{2nd} \times (\min x_k - r_{nk}), & \text{if } \beta_{nk}^{1st} \geq 0 \\ \hat{\beta}_{nk,np}^{2nd} \times (r_{nk} - \max x_k), & \text{if } \beta_{nk}^{1st} < 0 \end{cases} \quad \text{Eq. (37)}$$

Kivetz, Netzer, and Srinivasan (2004) captured the loss of respondent n for an attribute, but they did not suggest a reference points shifting rule; they defined the loss perceived by consumer n for attribute k as the difference between the level of attribute k for the alternative and the most inferior attribute level in choice set S. If the minimum and maximum levels of attribute k, reflected in Equation (37), are limited to the choice set S, as in Kivetz et al. (2004), it can be represented as Equation (38). However, as for orthogonal and efficient design used to construct a discrete choice experiment, the number of levels of attributes reflected in all choice sets are recommended to be the same, where Equation (37) and Equation (38) are identical.

$$ILA_{nk} = \begin{cases} \hat{\beta}^{2nd}_{nk,np} \times (\min x_{ks} - r_{nk}), & \text{if } \beta^{1st}_{nk} \geq 0 \\ \hat{\beta}^{2nd}_{nk,np} \times (r_{nk} - \max x_{ks}), & \text{if } \beta^{1st}_{nk} < 0 \end{cases} \quad \text{Eq. (38)}$$

Next, given that a consumers' choice is affected by the order of importance for attributes according to lexicography and EBA in decision strategy theories (Bettman & Park, 1980; Tversky, 1969; Tversky, 1972), as ILA_{nk} for attribute k becomes higher, it has greater influence on the respondent's decision-making process. Thus, the initial criterion attribute for reference points shifting is k satisfying $\underset{k}{\text{arc}\max} ILK_{nk}$, which is different for each respondent. Consequently, in the process of evaluating the alternative, if the level of the attribute with the highest importance of loss aversion is equal or superior to the reference point, the reference point of the attributes with relatively lower loss importance of loss aversion is shifted. To represent this, this study considers the following cases in the process of setting the shifting of the reference point.

First, the attribute with the highest ILA_{nk} for respondent n is defined as k_m and the corresponding reference point as r_{nk_m}. In this case, where level x_{jk_m} for attribute k_m

of alternative j is inferior to the respondent's reference point r_{nk_m}, the respondent has no enticement to shift reference points and they maintain the reference points as r_{nk} for other attributes k, other than k_m. On the other hand, when level x_{jk_m} for attribute k_m is superior to the reference point r_{nk_m}, there is an enticement to shift reference points for other attributes, because the respondent wants to avoid the losses of the attribute that they consider most important. In this regard, the degree of shifting for reference points of other attributes by eliminating loss for the most important attribute is set according to the proportion of ILA_{nk_m} in ILA_{nk} for all attributes, which is the relative importance of loss aversion, as represented in Equation (39). In addition, the reference points shifting is constrained so that a new reference point exists between the minimum and maximum levels for attribute k of choice sets in the discrete choice experiment to reflect reality (Swait, 2001).

If $(x_{jk_m} - r_{nk_m}) \times \hat{\beta}^{1st}_{nk_m} \geq 0$,

$$\tilde{r}_{nk} = \begin{cases} \min\left[\min x_k, r_{nk} - \left(|\min x_k - r_{nk}| \times \frac{ILA_{nk_m}}{\sum_{k=1}^{K} ILA_{nk}}\right)\right]_{I(\hat{\beta}^{1st}_{nk}>0)} \\ \min\left[\max x_k, r_{nk} + \left(|r_k - \max x_k| \times \frac{ILA_{nk_m}}{\sum_{k=1}^{K} ILA_{nk}}\right)\right]_{I(\hat{\beta}^{1st}_{nk}<0)} \end{cases} . \quad \text{Eq. (39)}$$

Otherwise,

$$\tilde{r}_{nk} = r_{nk}.$$

In this case, the relative importance of loss aversion is represented as Equation (40).

$$RIL_{nk_m} = \frac{ILA_{nk_m}}{\sum_{k=1}^{K} ILA_{nk}} \quad \text{Eq. (40)}$$

In addition, there is a case in which reference points are shifted according to the sequence of loss aversion importance, which can be represented as Equation (41).

If $(x_{jk_m} - r_{nk_m}) \times \hat{\beta}^{1st}_{nk_m} \geq 0$,

$$\tilde{r}_{nk_s} = \begin{cases} \min\left[\min x_{k_s}, r_{nk_s} - \left(|\min x_{k_s} - r_{nk_s}| \times \frac{\sum_{l=1}^{s-1} ILA_{nk_l}}{\sum_{k=1}^{K} ILA_{nk}}\right)\right]_{\mathrm{I}(\hat{\beta}^{1st}_{nk_s} > 0)} \\ \min\left[\max x_{k_s}, r_{nk_s} + \left(|r_{k_s} - \max x_{k_s}| \times \frac{\sum_{l=1}^{s-1} ILA_{nk_l}}{\sum_{k=1}^{K} ILA_{nk}}\right)\right]_{\mathrm{I}(\hat{\beta}^{1st}_{nk_s} < 0)} \end{cases} \cdots\cdots\text{Eq. (41)}$$

$$s.t.\ ILA_{k_{l-}} = 0, \text{ if } \mathrm{I}(ILA_{k_{l+}} > ILA_{k_l})(x_{jk_{l+}} - r_{nk_{l+}}) \times \hat{\beta}^{1st}_{nk_{l+}} < 0$$

Otherwise,

$$\tilde{r}_{nk_s} = r_{nk}.$$

If the level of attribute with the higher importance of loss aversion is not satisfied, that is, its losses are not eliminated, ILA_{nk_l} for the attributes that follow in the order of importance of loss aversion is not considered (Tversky, 1969). It is noteworthy that through simple constraints, Equation (41) about the sequential reference point shiting rule can include Equation (39) about a single reference points shifting rule for the attribute with the highest importance of loss aversion.

Next, Equations (39) and (41) are reference points shifting rules that are appropriate for cases in which the respondent's reference points exist for all attributes of the alternative. However, there may be some attributes that do not have an appropriate reference point. Accordingly, when the reference points shifting rule is applied for only some of the attributes, it is necessary to consider a weighted value ω_{nk_r} to prevent the reference point from being shifed too far. In this study, Equation (42), which identifies the relative importance of an attribute in the discrete choice model, is used to calculate the importance of the attributes, whose reference points are considered for shifting, relative to all attributes of the alternative. The relative importance of the attribute can be obtained by using the part-worth of each attribute; the part-worth of attribute k is the absolute value of that calculated by multiplying the difference between the maximum and minimum levels of attribute k, by estimated parameter $\hat{\beta}_{nk}$ for attribute k (Kim et al., 2006).

$$RI_{nk_r} = \frac{part-worth_{k_r}}{\sum_k part-worth_k} \times 100 \quad \text{Eq. (42)}$$

Then, the sum of the relative importance of the attributes derived from Equation (42) is used to set a weighted value ω_{nk_r}, as in Equation (43).

$$\omega_{nk_r} = \sum_{k_r} RI_{nk_r} \quad \text{Eq. (43)}$$

A flexible reference points shifting rule is established, as in Equation (44), if a weighted value, ω_{nk_r} is reflected in equation (41). In this case, $\omega_{nk_r} = 1$ when all attributes are considered, and Equations (44) and (41) are identical.

If $(x_{jk_m} - r_{nk_m}) \times \hat{\beta}^{1st}_{nk_m} \geq 0$,

$$\tilde{r}_{nk_s} = \begin{cases} \min\left[\min x_{k_s}, r_{nk_s} - \left(|\min x_{k_s} - r_{nk_s}| \times \dfrac{\sum_{l=1}^{s-1} ILA_{nk_{rl}}}{\sum_{k_r=1} ILA_{nk_r}} \times \omega_{nk_r} \right) \right]_{\mathrm{I}(\hat{\beta}^{1st}_{nk_s} > 0)} \\ \min\left[\max x_{k_s}, r_{nk_s} + \left(|r_{k_s} - \max x_{k_s}| \times \dfrac{\sum_{l=1}^{s-1} ILA_{nk_l}}{\sum_{k_r=1} ILA_{nk_r}} \times \omega_{nk_r} \right) \right]_{\mathrm{I}(\hat{\beta}^{1st}_{nk_s} < 0)} \end{cases} \quad \text{Eq. (44)}$$

$$s.t.\ ILA_{k_{l-}} = 0,\ \text{if}\ \mathrm{I}(ILA_{k_{l+}} > ILA_{k_l})(x_{jk_{l+}} - r_{nk_{l+}}) \times \hat{\beta}^{1st}_{nk_{l+}} < 0$$

Otherwise,

$$\tilde{r}_{nk_s} = r_{nk}.$$

If reference points shifting rule set as in Equation (44) is reflected in Equation (35), which is the reference-dependent choice model based on consistency, an advanced reference-dependent choice model is established, as represented Equation (45). The advanced reference-dependent choice model can provide a more profound understanding about consumer behavior by incorporating heuristics, such as the reference point effect and the context effect in the discrete choice model, unlike the existing reference-dependent choice model.

$$
\begin{aligned}
U_{nj}^{3\text{rd}} &= \sum \beta_{nk_{sg},p}^{3\text{rd}} (x_{jk_{sg}} - \tilde{r}_{nk_{sg}})_{\mathrm{I}(x_{jk_{sg}} \geq r_{nk_{sg}})} + \sum \beta_{nk_{sg},np}^{3\text{rd}} \mid x_{jk_{sg}} - \tilde{r}_{nk_{sg}} \mid_{\mathrm{I}(x_{jk_{sg}} < r_{nk_{sg}})} \\
&+ \sum \beta_{nk_{sh},p}^{3\text{rd}} \mid x_{jk_{sh}} - \tilde{r}_{nk_{sh}} \mid_{\mathrm{I}(x_{jk_{sh}} < r_{nk_{sh}})} + \sum \beta_{nk_{sh},np}^{3\text{rd}} (x_{jk_{sh}} - \tilde{r}_{nk_{sh}})_{\mathrm{I}(x_{jk_{sh}} \geq r_{nk_{sh}})} \\
&+ \sum \beta_{nk,p}^{3\text{rd}} \mid x_{jk} - \tilde{r}_{nk} \mid_{\mathrm{I}[(\beta_{nk}^{1\text{st}} \geq 0 \,\&\, x_{jk} \geq r_{nk}) \text{ or } (\beta_{nk}^{1\text{st}} < 0 \,\&\, x_{jk} < r_{nk})]} \\
&+ \sum \beta_{nk,np}^{3\text{rd}} \mid x_{jk} - \tilde{r}_{nk} \mid_{\mathrm{I}[(\beta_{nk}^{1\text{st}} < 0 \,\&\, x_{jk} \geq r_{nk}) \text{ or } (\beta_{nk}^{1\text{st}} \geq 0 \,\&\, x_{jk} < r_{nk})]} + \varepsilon_{nj}^{3\text{rd}}
\end{aligned}
\quad \cdots\cdots \text{Eq. (45)}
$$

In general, a model considering the context effect requires estimation of additional parameters. However, the advanced reference-dependent choice model has the same number of parameters as that of the existing reference-dependent choice model and the reference-dependent choice model based on consistency; therefore, the log-likelihood value or McFadden's pseudo ρ^2 can be used simply to compare and evaluate the goodness-of-fit of the models.

The basic framework of the methods proposed in this study is the same as that of the discrete choice model. The framework implies that utility maximization behavior, which is the basis of discrete choice models, is a compensatory decision rule, under which consumers perform trade-offs between attributes in choosing alternatives that provide the highest utility (McFadden & Train, 2000). However, if the non-compensatory decision rule and simplified decision strategies are reflected in the discrete choice model, the basic utility maximization framework cannot be applied. In other words, to consider a non-compensatory decision rule in the standard economic model, decision strategies and constraints should be added as well as the deterministic term of utility consisting of attributes (Swait, 2001). However, the existing reference-dependent choice model, in which the reference point effect is reflected in the discrete choice model, considers asymmetric preferences in the framework of the RUT. Its key hypothesis is that the level of the attribute can be framed as domains of gains and losses compared with their reference points and consumers choose an alternative to maximize utility through trade-offs between the gains domain and the losses domain for each attribute (DeBorger & Fosgerau, 2008; Tversky & Kahneman, 1991; Van de Kaa, 2010). In this respect, the reference-dependent choice model based on consistency proposed in this study divides attribute levels into the preference domain and non-preference domain, instead of gains and losses, and examines respondents' asymmetric preferences for attributes assuming trade-offs between the domains; thus, the RUM framework can be applied in the same way as the existing reference-dependent choice model. In addition, the reference points shifting rule considering the context effect adjusts only domains of preference and non-preference and thus, the RUM framework can also be applied to the advanced reference-dependent choice model, unlike the non-compensatory decision rule, which considers only a part of attributes. In summary, the methods proposed in this study do not require a new estimation process, because simulated maximum likelihood estimation or Bayesian estimation can be used for analysis.

Chapter 4. Empirical Studies

Reflecting the reality of behavior in a model for the analysis of preferences of decision-makers, such as consumers, increases the performance of an empirical model and enables better understanding about the behavior of the consumers (Chorus, 2012). In particular, the integration of the loss aversion effect, which can be explained by the reference point effect, with the standard economic model, significantly improves performance of the model (Hardie et al., 1993). Furthermore, a method consistent with the actual decision-making process not only provides more information but also produces unbiased estimation results, which in turn leads to better corporate strategy and government policies. The models proposed in this dissertaion enable consistent analysis of reference-dependent and asymmetric preferences for all attributes of the consumer and a more accurate reflection of the reality of the decision-making process by including the context effect as well as the reference point effect.

This chapter applies the methods proposed in Chapter 3 to the smartphone market (marketing), vehicle market (energy), and telemedicine (healthcare) to analyze consumers' asymmetric preferences for attributes of each alternative and to examine the goodness-of-fit and validity of the models. Specifically, the reference-dependent choice model based on consistency and the advanced reference-dependent choice model, which includes the reference points shifting rule based on loss aversion and decision strategies, are applied to the three empirical studies. For an empirical analysis, this study use SP

(Stated Preference)-based data from the discrete choice experiment to compare the results of the preference analysis and model fit of the existing choice models and the models proposed by this study. Each model is as follows: 1) the standard mixed logit model is represented as S-Model, 2) the existing reference-dependent choice model as R-Model-B, 3) the reference-dependent choice model based on consistency as R-Model-C, and 4) the reference-dependent choice model based on context as R-Model-S. According to the considered number of loss aversion importance, R-Model-S is designated as R-Model-S1, R-Model-S2, and R-Model-S3, etc. Furthermore, the arguments made in the preceding studies related to this study, other than the model fit are empirically tested using the results of the consumer preferences derived from each model.

It is worthwhile to examine the topics related the consumers' reference-dependent choices discussed in a wide range of areas, including marketing, prior to the empirical analysis using the methods proposed in this study. First, one of the most important topics in marketing, brand loyalty, is important in terms of corporate strategy. Brand loyalty is associated with the endowment effect, explained in Section 2.2.2, and is the central agenda in the smartphone market. Brand loyalty is closely connected to switching costs and peer effect. As for the telemedicine service market, it is necessary to adopt an innovation acceptance strategy related to the status quo effect, described in the reference-dependent theory in Section 2.2.2. Consumers are often hesitant to adopt innovative technology and service that would deliver better performance than the current state, because of the tendency to maintain the status quo. Successful introduction of new innovation is a major concern of the government and corporations. Against this backdrop, this chapter examines the existing literature on the various topics related to the reference-dependent choice model and present methods to explore the topics.

4.1 Literature Review of Topics Related to Loss Aversion

4.1.1 Switching Cost and Peer Effect on Brand Loyalty

Loss aversion, explained by the reference point effect, can occur regardless of whether risks are involved. An example of loss aversion in a choice under riskless is the endowment effect (Thaler, 1980). This effect can be understood as a symptom of the loss aversion effect, which is caused by reference-dependent effect (Tversky & Kahneman 1981). According to the definition (Thaler, 1980), an endowment effect for a brand occurs when consumers buy and possess a product of the brand. In other words, consumers' endowment effect for a brand can be explained by the loss aversion effect. Therefore, it is expected that loyal customers who tend to maintain the same brand have a larger loss aversion magnitude for the brand attribute than do consumers who switch brands. Consequently, a reference point is a key determinant in the brand choice by consumers (Zhou, 2011), and reference dependence and loss aversion have significant implications for the understanding of brand preferences and competition among brands (Hardie et al., 1993).

The brand is the most valuable asset of the manufacturer and the brand value perceived by the consumer is formed based on the characteristics of the product or service.

In addition, because of the endowment effect, consumers are more likely to stick with the brand they possess than to switch to a new brand. The behavior of sticking to the brand of the product they currently possess is mainly determined by brand loyalty. Brand loyalty is formed based on satisfaction with a specific brand and forms a favorable attitude and commitment toward the brand. Brand loyalty encourages consumers to purchase the same brand repeatedly in the future (Hansen, Beitelspacher, & Deitz, 2013). The consumer who repeates purchases from the same brand is defined as a loyal customer (Ballantyne, Warren, & Nobbs, 2006). It has been found that when consumers are satisfied with a product or service of a specific brand, they tend to lead other consumers around them to become interested and purchase the brand through positive word-of-mouth communication (Azad & Safaei, 2012).

Word-of-mouth, which occurs when consumers share their consumption experiences with others, is information gained from real experience and is considered more trustworthy than promotional information (Godes & Mayzlin, 2004). Furthermore, it has been found that the opinions of other consumers through word-of-mouth communications, as well as their own experience, have a significant impact on subsequent decisions to purchase and possess a product (Yi & Ahn, 2017). Because of such a peer effect, consumers can become interested in a specific brand. Above all, as consumers share information with others almost every day, or real-time, both online and offline (Kim, Briley, & Ocepek, 2015), peer effect can be an important factor in the decision-making process. Along with advances of communication technology, including online community, smartphones, and social networking services, word-of-mouth is becoming increasingly important (Yi & Ahn, 2017).

Peer effect, such as word-of-mouth effect, refers to the influence of an individual's choice by the purchase of products or assets of his or her peers, and is widely observed in the economic activity of consumers (Bursztyn, Ederer, Ferman, & Yuchtman, 2014). Thus, it is necessary for corporations to understand the implications of peer effect, such as word-of-mouth effect, in the marketing field (Dellarocas, 2006). In particular, peers with high innovativeness can influence consumers' new brand choice more significantly. Consumers with high innovativeness provide opinions to others and influence the diffusion of a product (Clark, Goldsmith, & Goldsmith, 2008). Consequently, consumers with high innovativeness play an important role in the diffusion of products (Rogers, 2010).

4.1.2 Status Quo Bias for Innovation Acceptability

In general, consumers are known to have a strong tendency to maintain the status quo (Samuelson & Zeckhauser, 1988). Status quo bias may lead consumers to underestimate the value of innovative services (Falk, Schepers, Hammerschmidt, & Bauer, 2007). As such, consumers often refuse to embrace innovation because of the status quo effect, and even reject alternatives that outperform current alternative (Gourville, 2006). Since the introduction of innovation generally involves additional initial costs, it is important to find ways to reduce individuals' reluctance to switch products or services because of higher costs, and to increase their acceptability (Kim & Crompton, 2002). A strategy for the introduction of innovative products or services is to influence individuals' reference points or to ensure that the status quo is perceived as a loss. First, governments and corporations can promote policy implementation by encouraging consumers to set goals or influence their reference point if goal-based reference point setting is important (Heath, Larrick, & Wu, 1999). Shifting reference point of some consumers through goal-based intervention also has the advantage of changing the behavior of other consumers through peer effect without providing incentives (Gerarden, Newell, & Stavins, 2017).

Another strategy of overcoming the rejection of an innovation is to set an innovation as default (Gourville, 2006). In general, a default refers to an option automatically accepted when consumers are not actively choosing alternatives (Brown & Krishna, 2004). It is especially known to help overcome the status quo bias of decision-making (Kuester, Hess, & Herrmann, 2015). This default-setting can be instrumental in implementing government policies or in releasing innovative products and services in the market (Kuester et al., 2015). In summary, policy messages can be more effectively delivered if the status quo can be framed as a loss for consumers compared with the innovation (Cornforth, 2009).

4.2 Application Methods of Topics related to Loss Aversion

4.2.1 Switching Cost and Brand Loyalty

Brand is an attribute for which the preferred direction is different, and as examined in Section 1.2 and 3.2, the existing reference-dependent choice model may produce biased estimation values for brand loyalty and brand-switching cost. By contrast, the advanced reference-dependent choice model based on consistency can yield unbiased values for brand loyalty and switching cost. Using estimated parameters from Equation (35), brand loyalty and switching cost can be represented as Equations (46) and (47), respectively.

$$\text{Brand Loyaty for Brand } b = \hat{\beta}^{\text{2nd}}_{nk_b,np} / \hat{\beta}^{\text{2nd}}_{nc,p} \quad \text{Eq. (46)}$$

$$\text{Switching Cost from Brand } b_1 \text{ to Brand } b_2 = MWTA_{b_1} - MWTP_{b_2} = \frac{1}{N}\sum\left(\hat{\beta}^{\text{2nd}}_{nk_{b_1},np} / \hat{\beta}^{\text{2nd}}_{nc,p} - \hat{\beta}^{\text{2nd}}_{nk_{b_2},p} / \hat{\beta}^{\text{2nd}}_{nc,np}\right) \quad \text{Eq. (47)}$$

Indeed, if the research purpose is focused on endowment effect, brand loyalty can be analyzed using the existing reference-dependent choice model. In other words, attribute levels can be divided simply into the losses of the current brand and the gains of a new brand. In this division, the parameter in the case of the tendency to hold on to the current brand is defined as brand loyalty, and the parameter in the case of obtaining a new brand can be defined as interest in other brands. For the analysis of brand interest and loyalty, a model is set using the existing reference-dependent choice model, as represented in

Equation (48).

$$U_{nj} = \beta_{nk_B,p}(x_{jk_B} - r_{nk_B})_{\mathrm{I}(x_{jk_B} \geq r_{nk_B})} + \beta_{nk_B,np} \mid x_{jk_B} - r_{nk_B} \mid_{\mathrm{I}(x_{jk_B} < r_{nk_B})} + \sum_{k \neq k_B} \beta_{nk} x_{jk} + \varepsilon_{nj} \quad \text{Eq. (48)}$$

Here, $\beta_{nk_B,p}$ is a parameter representing the degree of preference for gaining a new brand, and $\beta_{nk_B,np}$ is a parameter representing the degree of non-preference for losing the current brand.

4.2.2 Peer effect and Brand Loyalty

Equation (49), which is in the form of a function for social network analysis, can be used to reflect the influence from peers with high innovativeness for brand loyalty and switching (Wang, Aribarg, & Atchadé, 2013).

$$\sum_{o=1}^{O} S_{b_o} / \sum_{p=1}^{P} S_{b_P} \quad \cdots\cdots \text{Eq. (49)}$$

When the peer effect of Equation (49) is reflected as an interaction term in Equation (48) indicating brand interest and loyalty, the model is represented as the following Equation (50).

$$
\begin{aligned}
U_{nj} = & \sum \left\{ \beta_{nk_B,p} + \alpha^{o}_{nk_B,p} \left(\sum\nolimits_{o=1}^{O} S_{B_o} / \sum\nolimits_{f=1}^{F} S_{B_f} \right) \right\} (x_{jk_B} - r_{nk_B})_{\mathrm{I}(r_{ok_B} = x_{jk_B} \geq r_{nk_B})} \\
& + \sum \left\{ \beta_{nk_B,np} + \alpha^{o}_{nk_B,np} \left(\sum\nolimits_{o=1}^{O} S_{B_o} / \sum\nolimits_{f=1}^{F} S_{B_f} \right) \right\} | x_{jk_B} - r_{nk_B} |_{\mathrm{I}(x_{jk_B} < r_{nk_B} = r_{ok_B})} \quad \cdots \text{Eq. (50)} \\
& + \sum_{k \neq k_B} \beta_{nk} x_{jk} + \varepsilon_{nj}
\end{aligned}
$$

Here, S_{B_f} denotes the level of satisfaction for the currently owned brand by all peers (f), and S_{B_o} denotes the level of satisfaction for the currently owned brands by peers who have high innovativeness (o). Satisfaction here is an abstract construct—an accumulation of a consumer's total consumption experiences of an alternative, such as products or services (Johnson, Anderson, & Fornell, 1995).

4.2.3 Status Quo Effect and Innovation Strategy

In general, consumers have high expectations about the introduction of a new innovative technology or service. When the initial level of innovative technology does not satisfy the expectation, which serves as a reference point of the consumer, acceptance of the innovation decreases, because of the loss aversion effect. The reference point effect, status quo effect, and loss aversion effect on expectations can be integrated to represent a low level of innovation acceptance, as illustrated in Figure 8. When the initial level of an innovative technology is at Initial point 1 of Figure 8, it is lower than expectations in terms of quality and price; successful introduction of the innovation cannot be guaranteed.

In particular, as for Initial point 1, if the reference point is set as the expectation level, not as the current state, then innovation acceptance will be low even if the innovation delivers better quality than the status quo does.

In this case, the strategy that policymakers and corporate marketers can depend on is to lower consumers' reference point below the level of expectation or to shift it to the current state. A more realistic option with a higher acceptance of success is to set the consumers' expectation as the default and to provide them with information to evaluate the current state as well as the innovative technology. In Figure 8, if the expectation of the innovation is set as the reference point to evaluate the current state, then the status quo is a loss in quality, compared with Initial point 1, making it more likely for consumers to accept Initial point 1. As such, the evaluation of the current state compared to the expectation of innovation reflects the parameter for the non-preference domain and the difference between the expectation (reference point) and the current state as shown in the following Equation (51), in the choice probability equation which chooses the status quo, unlike the general form.

$$P_{n,status\,quo} = \frac{e^{V_{n,\,status\,quo}}}{\sum_i e^{V_{ni}}} = \frac{e^{\beta'_{nk,np}|x_{status\,quo,k} - r_{nk}|}}{\sum_i e^{V_{ni}}} \quad \text{Eq. (51)}$$

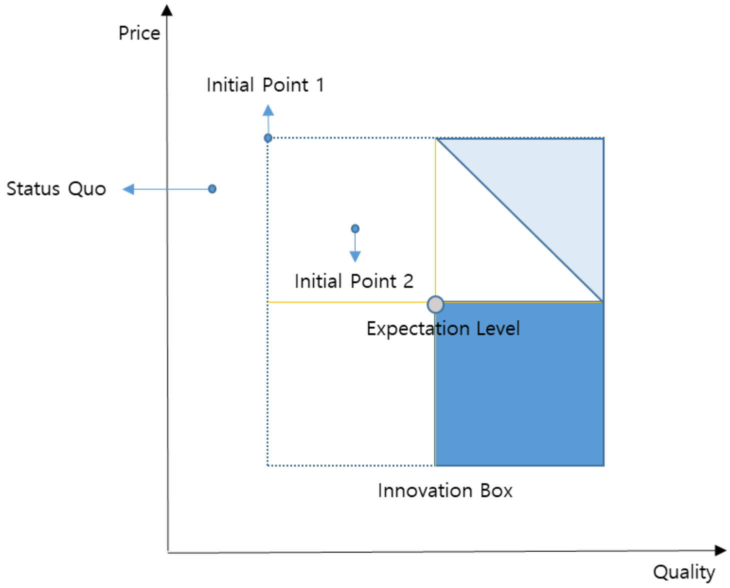

Figure 8. Low Innovation Acceptance Explained by the Loss Aversion Effect

4.3 Empirical Study 1: Smartphone Market of Marketing Field

4.3.1 Introduction

The global smartphone market is growing at a fast pace, and more than 5 billion people are predicted to have a smartphone by 2025 (Miller, 2012). This accounts for around 70% of the global population, and experts expect smartphones, with their convenience and multiple functions, to be used more universally than computers (Samaha & Hawi, 2016; Wrzus & Mehl., 2015). South Korea, the subject of this study, has one of the highest smartphone penetration rates of all countries in the world (Kim, Choi, Cho, Kim, & Koo, 2017). Despite the ongoing controversy over their price (Kim, Park, Cho, Kim, & Choi, 2017), the penetration rate keeps increasing. Along with the increase in demand, it is easy to observe that competition among smartphone manufacturers has become more heated than ever before.

Smartphones have a wide variety of functional attributes, such as screen size and operation system, as well as non-functional attributes, such as brand and price. In the early stage, new product development was focused on improving core technologies used in smartphones, including image quality or battery (Verganti, 2011), and as a result, smartphones in similar price ranges came to have similar levels of functional attributes. To outperform their rivals, leading smartphone manufacturers implemented a strategy to mount additional features, such as mobile payment (Oliveira, Thomas, Baptista, & Campos, 2016). However, the differentiation or competitiveness did not last owing to ease of imitation.

Therefore, it seems safe to say that brand loyalty will play a more important role than in the past in smartphone purchases. In particular, while it is complicated to compare functional attributes in the purchase decision-making process, brands are an easily visible feature. Furthermore, since a brand is closely related to the operating system, which is a smartphone's key functional features in terms of application, performance, and security, brands can greatly influence the consumer's choice of a smartphone. More than ever before, understanding of the consumer's brand loyalty is emerging as an important issue in marketing, along with the growth of the smartphone industry and rising competition (Yeh, Wang, & Yieh, 2016). Various methods can be applied to analyze the importance of brand among smartphone attributes; however, it is suitable to use a discrete choice experiment, which is a questionnaire survey including multiple attributes and the discrete choice model using the data obtained. In addition, the analysis of consumer preferences through the discrete choice model has the advantage of deriving consumers' preference parameters for each attribute and their relative importance, along with the MWTP (Koo, Kim, Hong, Choi, & Lee, 2012; Shin, Woo, Huh, Lee, & Jeong, 2014).

However, since most consumers possess smartphones in South Korea, it is better to reflect the reference point effect in the choice model to analyze preferences for a substitute for the product they currently possess (Kim et al., 2016). In addition, when consumers have strong loss aversion for brand owing to the endowment effect, the parameter for the brand attribute, derived using the discrete choice model, has limitation, as it tends to underestimate preference for brand they currently possess. Furthermore, it is possible for results inconsistent with economic definitions to be produced when using the existing reference-dependent choice model for the attributes for which the preferred direction is different.

Therefore, this study aimed to reflect the attributes of the smartphones consumers currently possess as reference points and to use the reference-dependent choice model based on consistency to derive consumers' asymmetric preferences for each attribute of the smartphone. Furthermore, the advanced reference-dependent choice model, including the reference points shifting rule, which incorporates the reference point effect and context effect, was used to examine the change of asymmetric preferences, such as loss aversion parameters, when behavioral reality is abundantly considered. Other than deriving major reference-dependent preferences, this study also examines brand loyalty and switching costs. In summary, this study makes a significant contribution to the field, as it provides theoretical implications for future study on consumer choice and preferences for smartphones as well as practical implications for smartphone manufacturers and the related industry to design effective marketing strategies.

4.3.2 Survey Data

This study collected data from the discrete choice experiment, which was performed between November and December 2017, on a sample of 1001 Koreans residing in Seoul and other large cities[4] and possessing a smartphone. The ages of the respondents were

[4]Gyoenggi (New towns) and five major cities (Busan, Incheon, Daegu, Daejeon, and Gwangju)

limited to 20–59 years, considering the ability to purchase a smartphone and understand the questionnaire. The survey was conducted through face-to-face interviews by Gallup Korea, which is a professional survey agency, and the interviewees were chosen through probability sampling with quota. Since the demographic characteristics, such as gender and age, of the population of the cities were known in advance, sampling was conducted according to the proportion of the population. Such quota sampling has the advantage of saving time and cost compared with probability sampling while providing a similar level of representativeness (Sudman, 1966).

The survey process is as follows. First, interviewers explained the features and types of smartphones to respondents; second, respondents were provided with explanations about the five attributes and the levels of alternatives; third, the alternatives were presented; fourth, the stated preferences of the respondents were recorded; finally, questions about demographic and psychographic characteristics of the respondents were asked. Of the 1001 respondents, 10 were eliminated, as they did not provide information about their current smartphones, and the final 991 samples were analyzed. The demographic characteristics of the respondents are shown in Table 2, and the attributes of the smartphones they use are shown in Table 3.

Table 2. Demographic Characteristics of the Smartphone Survey Respondents

Group		No. of Respondents	Rate
Gender	Male	500	50.5%
	Female	491	49.5%
Age	20–29	223	22.5%
	30–39	242	24.4%
	40–49	268	27.0%
	50–59	258	26.0%
Residing in	Seoul	432	43.6%
	Busan	142	14.3%
	Incheon	132	13.3%
	Daegu	106	10.7%
	Daejeon	64	6.5%
	Gwangju	64	6.5%
	Gyeonggi (New towns)	51	5.1%
Average Monthly Income	Less than 3 million KRW	65	6.6%
	3 million KRW-less than 4 million KRW	165	16.6%
	4 million KRW-less than 5 million KRW	285	28.8%
	5 million KRW-less than 7 million KRW	333	33.6%
	7 million KRW or more	143	14.4%

Table 3. Characteristics of the Smartphones Owned by Respondents

Div.		No. of Respondents	Rate
Brand	Samsung	686	69.2%
	Apple	145	14.6%
	LG	154	15.5%
	Other [a]	6	0.6%
Screen size	Less than 5.0 inches	136	13.7%
	5.0 inches-less than 5.5 inches	363	36.6%
	5.5 inches-less than 6.0 inches	403	40.7%
	6.0 inches or more	89	9.0%
Purchase price	Less than 400,000 KRW	334	33.7%
	400,000 KRW-less than 600,000 KRW	272	27.4%
	600,000 KRW-less than 800,000 KRW	232	23.4%
	800,000 KRW or more	154	15.5%
Storage capacity	16 GB	172	17.4%
	32 GB	395	39.9%
	64 GB	312	31.5%
	128 GB or more	112	11.3%
Recognition technology	Yes	575	58.0%
	No	416	42.0%

Note: [a]"Other" refers to brands (e.g., Huawei, Xiaomi, and Blackberry) other than Samsung, Apple, and LG.

The descriptions of the attributes and attribute levels of the smartphone alternatives used in the discrete choice experiment are presented in Table 4. Since the number of attributes of an alternative in a discrete choice experiment should be eight or less (Phelps & Shanten, 1978), all attributes, other than the five presented in Table 4, were assumed to be identical. The five attributes were chosen based on the existing literature, and the attribute levels were set based on the smartphones available in the market.

Table 4. Descriptions and Levels of Attributes of Smartphone Alternatives

Attributes	Description	Level
Brand	Manufacturers of major smartphones sold in the Korean market	Samsung, Apple, LG, Other
Screen Size (inches)	The size of the smartphone LCD screen. The LCD screen size of widely used smartphones are as follows: * iPhone 8: 4.7 inches, iPhone 8 Plus: 5.5 inches, Galaxy S8: 5.8 inches, Galaxy Note 8: 6.3 inches	4.5, 5.5, 6.5
Storage Capacity (GB)	The smartphone's built-in capacity, except external capacity, such as a Micro-SD card	32, 64, 128, 256
Recognition Technology	Technology for recognizing the user without using a password for unlocking the screen, a login to an application (app), or making a payment, etc. Examples include, fingerprint recognition, facial recognition, and iris recognition	Yes, No
Purchase Price (10,000 KRW)	The price of the terminal when paying a lump sum at the time of purchase, excluding the carrier subsidy	30, 65, 100, 135

A total of 384(4×3×4×4×2=384) alternatives could be obtained by mixing the five attributes and the levels of each attribute for smartphone, presented in Table 4. However, it was practically impossible to use all the 384 alternatives to analyze consumer preference, and thus, in this study, 16 alternative cards were constructed through orthogonal design, which is fractional factorial design. The 16 cards were grouped as four choice sets consisting of four cards each. Respondents were asked to choose an alternative that provides the highest utility out of the four alternatives; the task was performed four times. An example of the choice sets constructed in this study is shown in Table 5 (for all choice sets, refer to Appendix A).

Table 5. A Choice Set Example in the Discrete Choice Experiment of Smartphones

Attribute	Type A	Type B	Type C	Type D
Brand	Other	LG	Apple	Samsung
Screen Size	4.5 inches	4.5 inches	6.5 inches	5.5 inches
Storage Capacity	25 6GB	128 GB	32 GB	128 GB
Recognition Technology	Yes	No	Yes	Yes
Purchase Price	300,000 KRW	650,000 KRW	300,000 KRW	300,000 KRW
Choice	Type A	Type B	Type C	Type D

Consumer innovativeness is a psychological characteristic influencing the degree of adopting a high-tech product; consumers with a high level of innovativeness are more likely to look for new products and to buy them earlier than other consumers (Rogers, 2010). Highly innovative consumers are also experts with extensive knowledge and understanding of a specific product (Bruner & Kumar, 2007). In this study, peers with high innovativeness are defined as consumers with high expertise who provide information to others and influence other consumers' decisions to purchase high-tech products. To analyze peer effect, questions were asked about the brands of smartphones possessed by five peers, the peers' satisfaction with the brand, and the level of innovativeness (for specific questions, refer to Appendix A).

4.3.3 Estimation Results and Discussion

To use the reference-dependent choice model based on consistency, it is necessary to examine the preference heterogeneity and preferred directions of the respondents. To do this, this study used the mixed logit model to estimate the parameters for each attribute of smartphones, and the result is displayed in Table 6 as the S-Model. As expected, consumers preferred Samsung, Apple, and LG to other brands in general. Moreover, it was found that smartphones with larger storage capacity, providing of recognition technologies, and lower prices are preferred. On the other hand, parameters for screen size did not prove to be statistically significant. This is because some consumers preferred a bigger screen more, while others preferred a smaller screen.

The reference-dependent choice model based on consistency was used with the conditions of individual-level parameters obtained from the results of the mixed logit model analysis and the reference point for attributes possessed by the respondents at the time to analyze the asymmetric preferences of the respondents for the attributes of smartphones. The estimated results are shown in Table 7 as R-Model-C. To evaluate the model fit and consistency of R-Model-C thoroughly, asymmetric preferences were also analyzed using the existing reference-dependent choice model. The estimated results are illustrated in Table 6 as R-Model-B. As can be seen in the AIC and BIC statistics in Table 6, the existing reference-dependent choice model showed a better model fit than the standard mixed logit model. However, the estimation of a decrease in the size of smartphones did not prove to be statistically significant. This shows that, more than anything else, there is different preference among respondents for size reduction of smartphones, and it is difficult to define a size increase or decrease as loss. In other words, when estimating loss aversion parameters for attributes for which the preferred direction is different using the existing reference-dependent choice model, the results are not consistent with economic definitions. By contrast, smartphone brands, such as Samsung, Apple, and LG, show a very high rate of respondents who prefer them over other brands, the criterion of the dummy variables. In this case, the relative level of brands can be divided simply into a gains domain and a losses domain to induce estimates related to loss aversion. In other words, the asymmetric preferences for brands can be analyzed using the existing reference-dependent choice model. However, when the preference directions are analyzed based on the brands other than the specific brand, the rate of preference for the brand is lowered and the rate of non-preference is higher. In this case, as in the case of the size attribute, the estimated results may be inconsistent with the economic definition when using the existing reference-dependent choice model. Therefore, the reference-dependent choice model based on consistency should be used.

Table 6. Estimation Results for Smartphone Attributes in Existing Choice Models

Variables			S-Model	R-Model-B
Brand	Samsung		6.715***	
		Gain		4.271***
		Loss		-6.199***
	Apple		3.722***	
		Gain		2.225***
		Loss		-8.308***
	LG		3.250***	
		Gain		2.093***
		Loss		-3.744***
Screen Size (inches)			0.080	
		Increase		0.418***
		Decrease		0.180
Storage Capacity (100GB)			1.174***	
		Increase		0.789***
		Decrease		-1.585***
Recognition Technology			1.036***	
		Increase		0.895***
		Decrease		-0.731***
Purchase Price (million KRW)			-5.558***	
		Increase		-5.674***
		Decrease		2.524***
Log-likelihood			-3219.4341	-2917.7966
AIC			6452.8682	5863.5932
BIC			6496.8633	5932.1752

***Significant at the 1% level, **Significant at the 5% level, *Significant at the 10% level

The asymmetric preferences of consumers for smartphone brands, estimated by using

R-Model-C, are in order of Samsung, Apple, and LG in the preference domain, and in order of Apple, Samsung, and LG in the non-preference domain. In other words, consumers who possessed an Apple smartphone and preferred Apple showed the most sensitive non-preference for giving up the Apple brand. On the other hand, consumers who did not possess a Samsung smartphone and preferred the Samsung brand showed the most sensitive preference for gaining the Samsung brand. R-Model-B in Table 6 and R-Model-C in Table 7 have the same number of parameters, and log-likelihood value was used to compare the goodness-of-fit of the models. The comparison of log-likelihood values revealed that the model fit of the reference-dependent choice model based on consistency improved 10.7% from the existing reference-dependent choice model. In particular, as for R-Model-C, parameters for both preference and non-preference domains were found to be statistically significant. This is because the results related to loss aversion, derived from the division of attribute levels into preference and non-preference domains, do not conflict with economic definitions.

The asymmetric preferences of smartphone attributes were analyzed using the advanced reference-dependent choice model, considering the reference points shifting rule focused on the attributes with the highest importance of loss aversion. The estimation results are shown in Table 7 as R-Model-S1. As observed in the log-likelihood of R-Model-S1, the advanced reference-dependent choice model showed an improvement of the model fit by 22.3% and 13.0% over the existing reference-dependent choice model and the reference-dependent choice model based on consistency, respectively.

Table 7. Estimation Results for Smartphone Attributes Using the Proposed Reference-Dependent Choice Model Based on Consistency and Context (1)

Variables			R-Model-C	R-Model-S1
Brand	Samsung	Preference	4.616***	5.837***
		Non-preference	-7.149***	-6.254***
	Apple	Preference	2.450***	3.938***
		Non-preference	-9.624***	-7.274***
	LG	Preference	2.247***	3.016***
		Non-preference	-4.247***	-4.432***
Screen Size (inches)		Preference	1.260***	1.304***
		Non-preference	-1.084***	-1.564***
Storage Capacity (100GB)		Preference	1.236***	1.778***
		Non-preference	-2.183***	-2.794***
Recognition Technology		Preference	1.501***	1.899***
		Non-preference	-1.262***	-1.064***
Purchase Price (million KRW)		Preference	4.894***	4.963***
		Non-preference	-6.540***	-10.455***
Log-likelihood			-2605.1051	-2267.1911

***Significant at the 1% level, **Significant at the 5% level, *Significant at the 10% level

Next, this study analyzes consumers' asymmetric preferences by considering the order of importance of loss aversion for attributes using the advanced reference-dependent choice model. To this end, the ILA_{nk_l} of each respondent was calculated. The attribute with the highest importance of loss aversion was brand, followed by price, as Table 8 shows. It is noteworthy that the number of respondents for the attribute with the highest importance of loss aversion was largest for Samsung, but the ratio of respondents by brand possession was the largeest for Apple, as confirmed in Table 3. The respondents with LG smartphones were more likely to show lower importance of loss aversion to brand than to price.

Table 8. Number of Respondents in Order of Loss Aversion Importance

Variables		k_1	k_2	k_3	k_4	k_5
Brand	Samsung	460	210	15	2	-
	Apple	168	17	-	-	-
	LG	50	87	16	1	-
Screen Size		1	58	519	279	114
Storage Capacity		0	41	105	149	103
Recognition Technology		5	70	234	114	46
Purchase Price		307	506	72	30	11

The results of the consumers' asymmetric preference analysis, using the advanced reference-dependent choice model, which considered the order of importance of loss aversion and the reference points shifting rule, are shown in Table 9. The result when considering only the attributes with the highest importance of loss aversion is the aforementioned R-Model-S1 in Table 7. In Table 9, the result is represented as R-Model-S2 when considering up to the second attribute, as R-Model-S3 when considering up to the third attribute, and as R-Model-ST when considering total attributes. The results showed that the model fit of R-Model-S2, R-Model-S3, and R-Model-ST improved compared to R-Model-B, by 22.9%, 23.2%, and 23.0%, respectively. The improvement rate was 13.7%, 14.0%, and 13.7% for R-Model-S2, R-Model-S3, and R-Model-ST, respectively, when compared with R-Model-C. In summary, when shifting the reference points using the importance of loss aversion of three out of attributes, the model fit was the best, although the difference was slight. This result is in line with the assumption of the decision strategies, explaining the context effect, by indicating that consumers shift the reference point only for the part of attributes with a high level of loss aversion importance.

Table 9. Estimation Results for Smartphone Attributes Using the Proposed Reference-Dependent Choice Model Based on Consistency and Context (2)

Variables			R-Model-S2	R-Model-S3	R-Model-ST
Brand	Samsung	Preference	5.537***	5.601***	5.003***
		Non-preference	-6.069***	-6.253***	-5.957***
	Apple	Preference	3.723***	3.959***	3.619***
		Non-preference	-7.360***	-7.707***	-6.714***
	LG	Preference	3.097***	3.203***	2.937***
		Non-preference	-4.213***	-4.230***	-3.535***
Screen Size (inches)		Preference	1.304***	1.332***	1.258***
		Non-preference	-1.564***	-1.551***	-1.480***
Storage Capacity (100GB)		Preference	1.778***	1.934***	1.744***
		Non-preference	-2.794***	-2.591***	-2.666***
Recognition Technology		Preference	1.899***	1.897***	1.892***
		Non-preference	-1.064***	-1.189***	-1.125***
Purchase Price (million KRW)		Preference	4.963***	5.965***	5.345***
		Non-preference	-10.455***	-10.262***	-10.142***
Log-likelihood			-2248.4496	-2240.4753	-2247.2491

***Significant at the 1% level, **Significant at the 5% level, *Significant at the 10% level

Table 10 shows the loss aversion parameters in the reference-dependent choice model based on consistency (R-Model-C) and more advanced reference-dependent choice models (R-Model-S1 and R-Model-S3). Before examining the resulting loss aversion parameters, asymmetric preferences were validated through the ratio of estimated parameters in the preference and non-preference domains. Specifically, a t-test was performed under a null hypothesis ($\hat{\beta}_{k,np}^{2nd} / \hat{\beta}_{k,p}^{2nd} = \hat{\lambda}_k = 1$), and the result showed that the preference for all attributes was asymmetrical. The result for R-Model-C shows that the loss aversion parameters for screen size and recognition technology are smaller than 1. This means that consumers considered the level of preference domain as more important than that of non-preference domain for screen size and recognition technology in the process of choosing smartphones (Kim et al., 2016). On the other hand, the result for R-Model-S1 and R-Model-S3 shows that the loss aversion parameter for screen size is larger than 1, which means that the loss aversion parameter for screen size increases, considering reference points shifting. Moreover, the result of R-Model-C analysis revealed that the attributes with loss aversion parameters larger than 1, except the price attribute, had smaller loss aversion parameters when applying the reference points shifting rule, but a larger parameter for the price attribute. As explained in Section 1.2, the ratio of MWTA to MWTP, represented by the product of each loss aversion parameter for attributes other than price and price attribute, changed along with the loss aversion parameters for each attribute.

Table 10. Loss Aversion Parameter in the Proposed Reference-Dependent Choice Models

Variables	Loss Aversion Parameter		
	R-Model-C	R-Model-S1	R-Model-S3
Samsung (Brand)	1.549	1.072	1.116
Apple (Brand)	3.928	1.847	1.787
LG (Brand)	1.890	1.470	1.320
Screen Size	0.860	1.181	1.165
Storage Capacity	1.766	1.736	1.340
Recognition Technology	0.841	0.661	0.627
Purchase Price	1.335	1.595	1.720

Taking a closer look, the ratio of MWTA to MWTP was derived using R-Model-C, R-Model-S1, and R-Model-S3, as illustrated in Table 11. The estimated results for the ratio of MWTA to MWTP in each model were found to be bigger than 1. In particular, hyper-asymmetry between the MWTA and MWTP (e.g., Apple brand, in this analysis) is often seen in the existing reference-dependent choice model, which has been developed as an alternative of the discrete choice model, and can be relaxed by applying the reference points shifting rule. The changes in the ratio of MWTA to MWTP, analyzed using different models, are compared in Figure 9. The Apple brand, with the highest ratio of MWTA to MWTP among other brands, when estimated using R-Model-C, showed an overall decrease in the ratio of MWTA to MWTP when the reference points shifting rule was considered. The MWTA/MWTP for size was estimated around 1 by using R-Model-C, but the consideration of the reference points shifting rule roughly doubled the ratio. Above all, these changes were due to the change in loss aversion parameters for each attribute, as shown in Table 10. In addition, changes in loss aversion parameters for the price attribute according to economic definitions influenced the ratio of MWTA to MWTP. To put it simply, the loss aversion parameter for the Apple brand decreased significantly, and the loss aversion parameter for size increased slightly, but a rise in the loss aversion parameter for price decreased the ratio of MWTA to MWTP for the Apple brand and significantly increased the ratio of MWTA to MWTP for size.

Table 11. The Ratio of MWTA to MWTP in the Proposed Reference-Dependent Choice Models

Variables	MWTA/MWTP		
	R-Model-C	R-Model-S1	R-Model-S3
Samsung (Brand)	1.642	1.694	1.893
Apple (Brand)	4.753	3.020	3.063
LG (Brand)	1.936	2.387	2.385
Screen Size	1.098	1.957	2.036
Storage Capacity	2.026	2.789	2.214
Recognition Technology	1.057	1.836	1.783

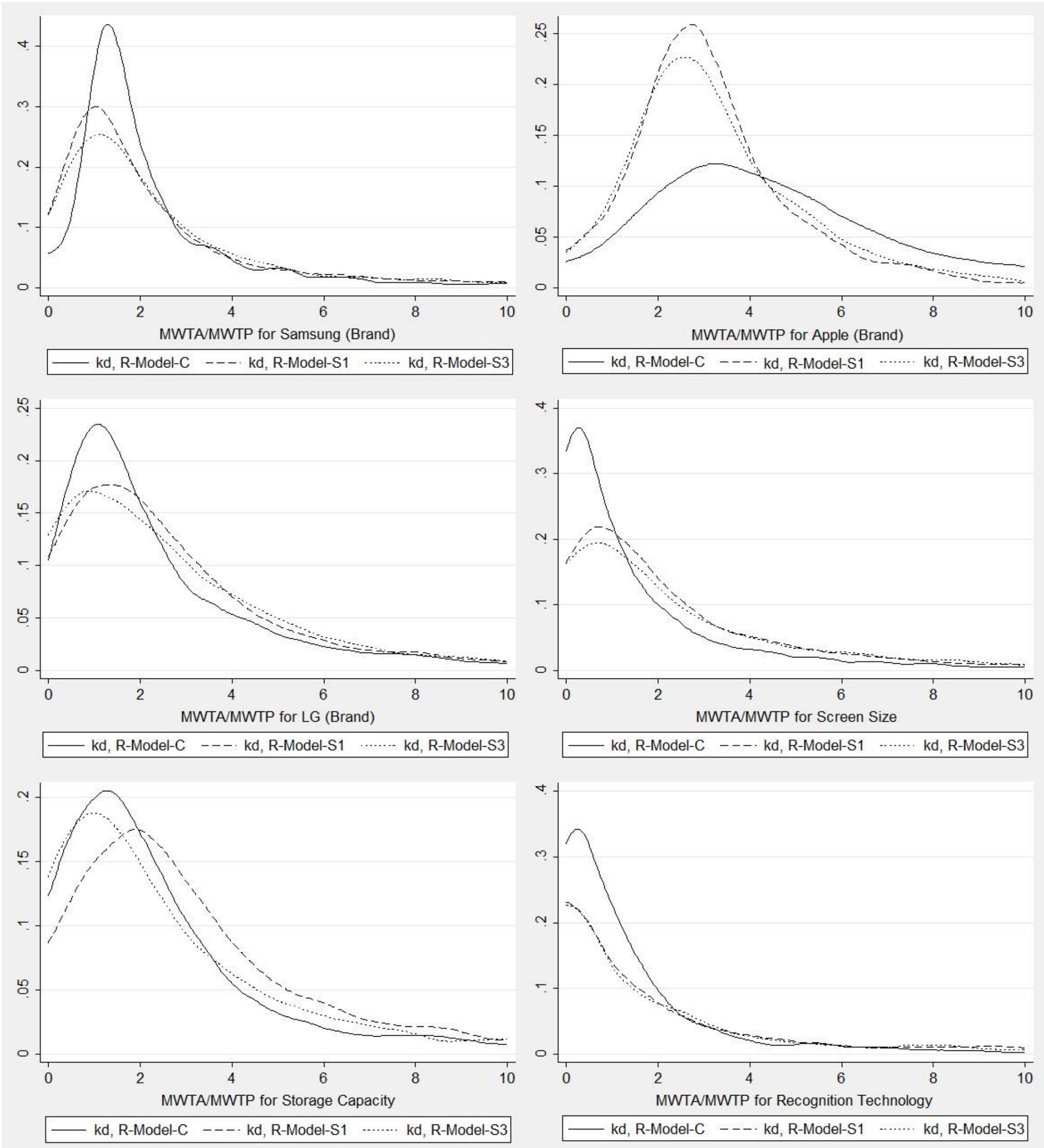

Figure 9. Change of the MWTA /MWTP in the Proposed Reference-Dependent Models

Next, brand-switching costs were investigated to evaluate brand loyalty for smartphones. The result is shown in Table 12. When using the reference-dependent choice model suggested in this study, brand-switching costs can be easily obtained using MWTA and MWTP with estimated parameters. The loss aversion effect, which can be explained by the reference point effect, explains the endowment effect, and brand loyalty, which is explained by these effects, causes changes between switching costs for each brand. This means that the higher are the asymmetric preferences and loss aversion, the higher are the brand loyalty and switching costs. Apple, the brand with the highest loss aversion parameters, shows high brand loyalty and switching cost.

Table 12. Brand-Switching Cost Calculated in the Advanced Reference-Dependent Model

Brand Switching	Switching Cost (unit, KRW)	
	R-Model-S1	R-Model-S3
Samsung→ Apple	532,928	614,454
Samsung→ LG	603,701	681,748
Apple→ Samsung	436,041	502,053
Apple→ LG	716,115	761,081
LG→ Samsung	94,939	141,973
LG→ Apple	305,786	319,431

Next, Apple's price increases, a hot issue in the smartphone market recently, is discussed to provide additional marketing implications by using the methods presented in this study. Specifically, this study examined repurchase probability by respondents currently in possession of an Apple product in the case of a higher price increase of the Apple brand than the reference price, using estimation values from the S-Model, R-Model-C, and R-Model-S3. As can be seen in Figure 10, S-Model predicts that repurchase probability is low at the time of price increase, but according to R-Model-C, repurchase probability is high owing to brand loyalty despite the raised price. However, the repurchase probability estimated by R-Model-S3, which reflects the behavior reality of consumers and shows better fit than the other two models, is located in the middle between those of S-Model and R-Model-C. This finding implies that the estimated results from S-Model or R-Model-C can lead to biased predictions when applied to corporate strategy, especially considering the outcome of empirical models.

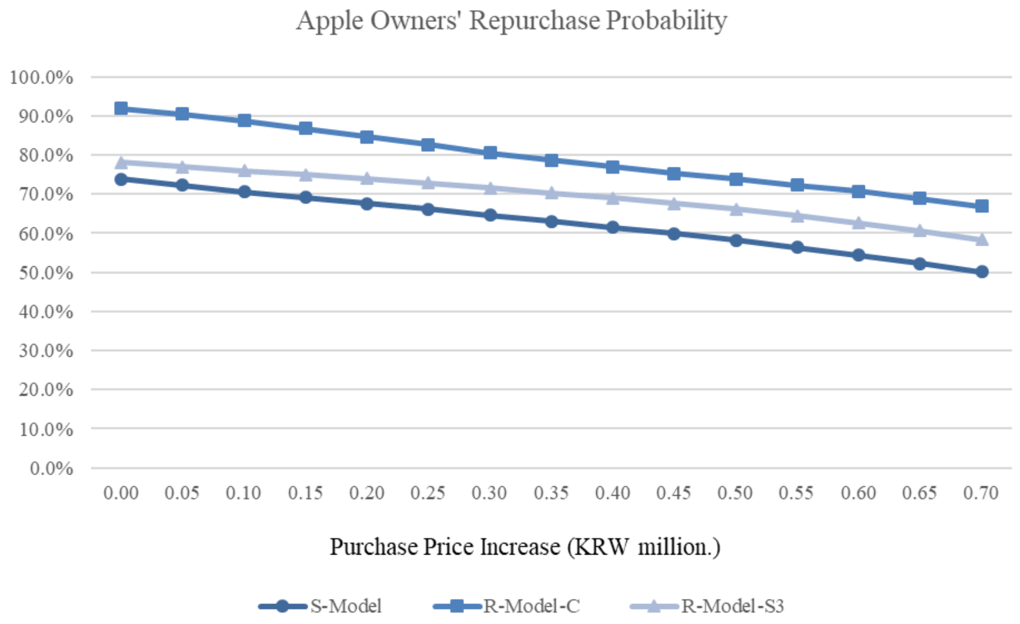

Figure 10. Repurchase Probability Based on Apple Brand Price Increase

Peer effect was examined in relation to brand loyalty. The result is shown in Table 13. The analysis result showed that as peers with high innovativeness become more satisfied with the brand of their smartphones, respondents tend to have higher interest in each of the brands they do not have. However, as for brand loyalty, the satisfaction with the brand of peers with high innovativeness was found to be statistically significant for the Apple brand only. Thus, brand image, shaped in relations with peers, greatly influences their choice of smartphones as well.

Table 13. Estimation Results of the Brand Interest, Brand Loyalty, and Peer Effect

Variables			Mean	Std. D
Brand	Samsung	Gain	4.109***	2.271***
		Loss	-6.488***	2.982***
	Apple	Gain	2.083***	2.011***
		Loss	-7.664***	4.072***
	LG	Gain	1.785***	1.555***
		Loss	-3.783***	1.813***
Highly Innovative Peers' Brand Satisfaction	Samsung	Gain	1.614***	1.643***
		Loss	-0.187	2.912***
	Apple	Gain	2.454***	1.619*
		Loss	-0.902**	2.042***
	LG	Gain	2.964***	2.738***
		Loss	-0.150	2.148***
Screen Size (inches)			0.107	0.814***
Storage Capacity (100GB)			1.068***	1.109***
Recognition Technology			1.120***	1.481***
Purchase Price (million KRW)			-5.502***	4.663***

***Significant at the 1% level, **Significant at the 5% level, *Significant at the 10% level

4.3.4 Conclusion and Implications

Consumers buy products based on those they possess at the time. Therefore, incorporating the reference-dependence theory into the discrete choice model, which is widely used to analyze consumer preferences, enables the analysis of asymmetric preferences for attributes constituting the product. However, using the existing reference-dependent choice model to analyze the attributes for which the preferred direction is different has limitations, as it represents inconsistency in the process of deriving the estimation results. Thus, this study analyzed the reference-dependent preferences for smartphones using the reference-dependent choice model based on consistency, suggested in this study. Furthermore, by using the advanced reference-dependent choice model that considers the reference points shifting rule, changes in asymmetric preferences were examined considering both the reference point effect and context effect.

The analysis result showed that the reference-dependent choice model based on consistency and the advanced reference-dependent choice model highly improved the model fit compared to the standard discrete choice model or the existing reference-dependent choice model. Consumers' asymmetric preferences to the attributes were also examined; loss aversion parameters were smaller than 1 for some attributes and larger than 1 for other attributes. In addition, the ratio of MWTA to MWTP was larger than 1 for all attributes, but there was a difference between the ratios derived from each model along with changes of loss aversion parameters.

In particular, brand is considered as an important attribute in consumer choice of smartphones. In regard this, brand loyalty is a consumer tendency influencing the continuous use of the brand currently possessed by the consumer and is of major concern for marketers. When using the standard discrete choice model, which is the symmetric form to analyze consumer preferences about smartphone attributes, brand preferences may be underestimated relative to brand loyalty. To prevent this problem, the reference-dependent choice model suggested in this study was used to examine consumers' brand loyalty toward smartphones as well. This study is significant, as it examined peer effect with high innovativeness as well as respondents' preferences in order to closely examine the brand loyalty and interests of consumers.

This study, however, has its limitations, as it analyzed consumer preferences under the assumption that consumers consider only the previous period when buying a new smartphone, based on the one they currently possess. Given that smartphones are regularly replaced, however, consumers' decision to purchase a new smartphone can be understood as a result of learning experience from buying multiple smartphones. The scope of this study was limited to using information on the smartphones currently possessed by consumers and the process of choosing a new smartphone. However, future studies would benefit from using real purchase data to reflect changing preferences over multiple purchases in the analysis. Moreover, when it comes to the analysis of consumer preference, the meaning of asymmetric preferences can be used in more diverse ways than those discussed in this study. In the follow-up study, asymmetric preferences for attributes are compared with a scenario analysis to propose a richer set of corporate strategies.

4.4 Empirical Study 2: Vehicle Market of Energy Field

4.4.1 Introduction

Despite the efforts of major Organisation for Economic Co-operation and Development countries to reduce greenhouse gas (GHG) emissions and a series of regulations, GHG released from vehicles employing internal combustion engines, such as gasoline and diesel engines, are still a serious problem. More than 95% of the vehicles in the world burn oil as fuel, which accounts for more than half of the total global oil consumption (Andersen, Mathews, & Rask, 2009). Under these circumstances, with the international community raising its voice for the reduction of GHG emissions, the automobile industry is starting to change (Hoyer, 2008). Research on vehicles powered by various sources has been actively explored, and electric vehicles are gradually gaining ground in the market thanks to persistent R&D investment and rising public awareness (Skerlos, 2010).

However, in reality, the spread of electric vehicles is slower than forecast by many related studies. The reasons for this can be discussed from technological and social aspects. From the technological perspective, the lack of infrastructure for charging such vehicles and mileage are major stumbling blocks for consumers (Egbue & Long, 2012). From the social perspective, the price of electric vehicles has been found to be a leading cause negatively influencing consumers’ willingness to buy an electric vehicle (Diamond, 2009). From the social perspective, the price of electric vehicles was found to be a leading cause negatively influencing consumers’ willingness to buy them. However, the share of electric vehicles in the automobile market is expected to grow with the recent progress of technology, making it cheaper to replace batteries along with mileage improvement (Hidrue, Parsons, Kempton, & Gardner, 2011).

Another characteristic of the electric vehicle market, other than technological and social factors, is that the vehicle types are mostly passenger cars, such as compact cars and sedans. Therefore, it is important to discuss the influence of the release of electric sport utility vehicles (SUVs) on the spread of electric vehicles. The spread of electric vehicles is ultimately affected by the choices of consumers, and it is necessary to analyze consumer preferences for electric vehicles to build an effective strategy to spread electric vehicles. Consumers, as they do for other goods, weigh various attributes of electric vehicles and make the final choice of a vehicle that maximizes their utility when making a purchase. Since an electric vehicle is a product in its initial stage in the market and there is no sufficient purchase data available, it is better to analyze consumer preferences using choice experiment data consisting of virtual alternatives (Train, 2009).

If the alternative being considered by the consumer is a substitute for a product that they already possess, the consumer does not choose a new product by considering only the presented attribute levels. In other words, consumers make a purchase decision after comparing the level of attributes of the product they possess with those of a new product to choose (Tversky & Kahneman, 1991). Unfortunately, there is no study dedicated to the analysis of consumers' asymmetric preferences for the attributes of electric vehicles using the reference point effect. Unlike previous studies on consumer preferences for electric vehicles, this study used the reference-dependent choice model proposed in this study to analyze consumers' asymmetric preferences for electric vehicle attributes by setting the attributes of the vehicle currently possessed as a reference points for some attributes considered important in choosing electric vehicles. Based on the estimation results, a scenario analysis was conducted for each attribute to suggest corporate marketing and government policies required to accelerate the pace of electric vehicle diffusion.

4.4.2 Survey Data

This study collected data using the discrete choice experiment to suggest policies needed to promote the diffusion of electric vehicles as well as to analyze consumer preferences. There are limited market data on products and services that are not widely spread in the market, such as alternative-fuel vehicles, including electric vehicles. The electric vehicle, the main analysis target of this study, is gradually increasing its market share since its release, but it is still in its initial stage with a very low market share, making it difficult to examine consumers' preferences using revealed preference market data only. Against this backdrop, it seems more suitable to conduct the discrete choice experiment whereby respondents are presented with a choice set consisting of the attributes of vehicle alternatives (including electric vehicles) that are similar to the actual choice situation.

In the experiment, 675 Koreans (aged 20–59 years) living in Seoul and other major cities[5] of South Korea were surveyed in May and June 2012 through face-to-face interviews by Gallup Korea, a professional survey organization. In South Korea, since an individual must be 20 years or older to buy a vehicle and the rate of vehicle purchase is very low for those ages over 60 years, the age of the respondents is limited to the group aged 20 to 59 years. The interviewees were chosen through quota sampling. Out of the 675 respondents, 547 currently in possession of vehicles were used for the final analysis. The demographic characteristics of the respondents and information about the vehicles they possessed are summarized in Tables 14 and 15, respectively.

Table 14. Demographic Characteristics of the Vehicle Survey Respondents

Group		No. of Respondents (%)
Gender	Male	264 (48.3%)
	Female	283 (51.7%)
Age	< 30	136 (24.9%)
	30–39	148 (27.1%)
	40–49	161 (29.4%)
	50–59	102 (18.6%)
Residing in	Seoul	210 (38.4%)
	Busan	76 (13.9%)
	Incheon	71 (13.0%)
	Daegu	62 (11.3%)
	Daejeon	46 (8.4%)
	Gwangju	41 (7.5%)
	Gyeonggi (New towns)	41 (7.5%)

[5] Gyoenggi (New towns) and five major cities (Busan, Incheon, Daegu, Daejeon, and Gwangju)

Table 15. Characteristics of Vehicles Owned by Respondents

Group		No. of Respondents (%)
Fuel type	Gasoline	378 (69.1%)
	Diesel	141 (25.8%)
	LPG	26 (4.8%)
	Hybrid	2 (0.4%)
Vehicle type	SUV (RV)	159 (29.1%)
	Sedan	388 (70.9%)
Purchase price of vehicle (10,000 KRW)	Avg. (SD)	2,424 (1,186)
Mileage per liter (km/*l*)		11.37 (2.85)

Next, the attributes of vehicles, and description and levels of the attributes are presented in Table 16. Attributes other than the six shown in the table were assumed to be identical. The six attributes were selected based on those considered important in previous studies on consumer preference for electric vehicles (Brownstone, Bunch, & Train, 2000; Potoglou & Kanaroglou, 2007).

Table 16. Description and Level of Attributes of Vehicle Alternatives

Attributes	Description	Levels
Fuel type	Power source of vehicle	Gasoline Diesel Hybrid Electricity (Battery)
Vehicle type	Type of vehicle	SUV (RV) Sedan
Fuel efficiency	Distance that can be traveled per liter (km/l)	10 km/*l* 20 km/*l* 40 km/*l*
Vehicle price	Purchase price except for insurance and taxes	25 million KRW 30 million KRW 35 million KRW 40 million KRW
Accessibility to gas/charging stations (%)	The ratio of gas/charging stations available when the number of gas stations is assumed to be 100.	100% 80% 50%
Availability of smart car options	Heightened driving safety, additional service linked to smart devices, Internet connection, etc.	Yes No

This study selected a total of 16 alternative cards through orthogonal design, which is fractional factorial design, of the alternatives that can be created by mixing the vehicle attributes and the level of each attribute. Subsequently, the 16 cards were grouped into four choice sets consisting of four cards each. An example of the choicesets used in this study is presented in Table 17 (for all choice sets, refer to Appendix B).

Table 17. A Choice Set Example in the Discrete Choice Experiment of Vehicles

Attribute	Type A	Type B	Type C	Type D
Fuel type	Gasoline	Diesel	Hybrid	Electricity
Vehicle type	Sedan	SUV(RV)	SUV(RV)	Sedan
Fuel efficiency	40 km/*l*	40 km/*l*	20 km/*l*	20 km/*l*
Vehicle price	25 million KRW	40 million KRW	40 million KRW	35 million KRW
Accessibility	50%	80%	50%	100%
Smart car options	No	Yes	Yes	No
Choice	Type A	Type B	Type C	Type D

4.4.3 Estimation Results and Discussion

Individual respondents' preference parameters for attributes were analyzed using the mixed logit model. The estimation result is shown in Table 18 as S-model. The analysis result revealed that the average consumer prefers hybrids the most out of all fuel types, followed by gasoline, diesel, and electricity. The parameters for fuel type can be interpreted as an average preference for fuel type when other attribute levels are identical (Mabit & Fosgerau, 2011). Furthermore, since attributes, such as fuel efficiency, vehicle price, and accessibility, are set as log-normal distribution, it was found that cheaper vehicles with better fuel economy and higher accessibility were preferred.

In addition, an asymmetric preference analysis was conducted using the existing reference-dependent choice model. The estimation result is presented in Table 18 as R-Model-B. As can be seen from the AIC and BIC statistics in Table 18, the existing reference-dependent choice model was better in terms of model fit than the mixed logit model, albeit slightly. However, the estimates of the gains domain for SUV was found to be statistically insignificant. This shows that, more than anything else, there is preference heterogeneity and difference of a preferred direction among respondents for gains of SUV, and it is more appropriate to apply the reference-dependent choice model based on consistency, proposed in this study. Thus, when respondents' preferences directions were quite different, as in the vehicle type attribute, unlike the brand attribute of smartphones in Section 4.3, the analysis of gains and losses could not produce meaningful statistics, although it suited the research purpose.

Table 18. Estimation Results for Vehicle Attributes Using the Existing Choice Model

Attribute and Domain			S-Model	R-Model-B
Fuel type	Gasoline		-0.407**	-0.027
(ref: Hybrid)	Diesel		-1.184***	-1.392***
	EV		-1.265***	-1.036**
SUV			0.006	
		Gain		-0.195
		Loss		-0.976***
Fuel efficiency (10 km/*l*)			0.786***	
		Increase		0.996***
		Decrease		-1.195***
Vehicle price (10 million KRW)			-0.996***	-1.047***
Charging accessibility (10%)			2.546***	
		Decrease		-1.036***
Smart car option			1.138***	1.661***
Log-liklihood			-2019.8519	-2018.5978
AIC			4055.7038	4057.1956
BIC			4098.9283	4100.2401

***Significant at the 1% level, **Significant at the 5% level, *Significant at the 10% level

The reference-dependent choice model based on consistency was used with the conditions of individual-level parameters obtained from the results of the mixed logit model analysis and the reference point for attributes possessed by the respondents at the time, to analyze the asymmetric preference of the respondents for the SUV attribute. The estimated results are shown in Table 19 as R-Model-C. The asymmetric preferences for the estimated vehicle types were more specifically examined using R-Model-C. The degree of non-preference for giving up the SUV when a consumer who was in possession of an SUV preferred an SUV was higher than the degree of preference for gaining a sedan when a consumer who was in possession of an SUV preferred a sedan. Furthermore, given the characteristics of the reference-dependent choice model based on consistency, the degree of non-preference for gaining the SUV when a consumer who was in possession of a sedan did not prefer an SUV was higher than the degree of preference for gaining an SUV when a consumer who was in possession of a sedan preferred an SUV.

The analysis result of asymmetric preferences in consideration of the reference points shifting rule is presented in Table 19 as R-Model-S. In this study, only vehicle type, fuel efficiency, and accessibility exist as reference points, and the attribute with the highest importance of loss aversion was set as a criterion for the reference points shifting rule. Furthermore, R-Model-C and R-Model-S of Table 19 show the difference in the number of model parameters,[6] and thus, the AIC and BIC statistics were used to evaluate the model fit, showing that R-Model-S1 had a slightly better fit, but to an insignificant

[6]R-Model-C estimated the parameters for the non-preference domain in which accessibility decreases, as accessibility to gas/charging stations was set with the current accessibility to gas stations as 100%.

margin. However, R-Model-C of Table 19, a reference-dependent choice model based on consistency, showed an improvement of model fit of 8.6% over R-Model-B of Table 18, which is the existing reference-dependent choice model.

Table 19. Estimation Results for Vehicle Attributes Using the Proposed Reference-Dependent Choice Models

Attribute and Domain			R-Model-C	R-Model-S
Fuel type	Gasoline		-0.579**	-0.750**
(ref: Hybrid)	Diesel		-1.099***	-1.007***
	EV		-1.628***	-1.592***
SUV		Preference	2.226***	2.558***
		Non-preference	-3.209***	-3.182***
Fuel efficiency (10 km/*l*)		Preference	0.911***	0.936***
		Non-preference	-1.454***	-1.064***
Vehicle price (10 million KRW)			-1.152***	-1.065***
Charging accessibility (10%)		Preference	-	0.469
		Non-preference	-3.108***	-3.748***
Smart car option			1.860***	1.550***
Log-liklihood			-1844.5561	-1840.6376
AIC			3709.1122	3703.2752
BIC			3763.1428	3750.6241

***Significant at the 1% level, **Significant at the 5% level, *Significant at the 10% level

The result of loss aversion parameters for SUV(RV) and fuel efficiency using the analysis of R-Model-C and R-Model-S are presented in Table 20. According to the estimation using R-Model-C, the loss aversion parameter for SUV(RV) was 1.442, while a decrease of 1 km/*l* in fuel efficiency negatively influenced consumer utility by 1.596

times more than an increase of the same size. Moreover, the estimation using R-Model-S revealed that the loss aversion parameters for both SUV and fuel efficiency decreased, with the former parameter larger than the latter. Together, loss aversion parameters were derived for each attribute using R-Model-C and R-Model-S, and all of them were larger than 1. This result is in line with the argument of the previous studies on the reference point effect that loss aversion parameters are in general larger than 1 (Tversky & Kahneman, 1992). In particular, the loss aversion parameter for SUV was the biggest in R-Model-S (1.244), which means it is highly likely to play a crucial role in the decision-making process of consumers (Masiero & Hensher, 2010).

Table 20. Loss Aversion Parameters in the Proposed Reference-Dependent Choice Models

Variables	Loss Aversion Parameter	
	R-Model-C	R-Model-S
SUV	1.442	1.244
Fuel efficiency	1.596	1.137

Since the parameter for the preference domain of the accessibility attribute was not statistically significant in R-Model-S,[7] this study used the estimated results of R-Model-C to conduct a scenario analysis. As a result, it was revealed that the market share of internal combustion engine vehicles, powered by gasoline and diesel, was overwhelmingly high in the automobile market, and the consumers preferred gasoline or

[7]For this reason, it is a possible that the number of samples for the preference domain of the accessibility attribute was insufficient.

diesel alternatives to electric vehicles. Therefore, more than anything else, it is necessary to increase the consumer utility of electric vehicles compared to internal combustion engine vehicles. Thus, the electric vehicle alternative and gasoline or diesel alternatives were compared and analyzed. First, changes in the net utility of consumers were analyzed while changing a specific attribute levels of the electric vehicle alternative. This is represented as the following Equation (52) (Allenby & Ginter, 1995).

$$U_{nj}^{*} = U_{nj} - U_{ni} > 0 \quad \text{Eq. (52)}$$

In this equation, j is an alternative with changes, and i is an alternative serving as a criterion. In this study, alternative j is electric vehicles, and as the level of attributes changes, the utility of electric vehicles also changes, and so does the rate of net utility for electric vehicles (U_{nj}^{*}). Based on this understanding, it is possible to indirectly predict the market share of electric vehicles relative to that of internal combustion engine vehicles for each scenario. Assuming that the level of attributes other than the six considered in this study are identical, the biggest difference between the two alternatives are fuel efficiency, price, accessibility to gas/charging stations, and vehicle type.

The number of charging stations for electric vehicles in South Korea is no more than 3% of that of gas stations. Therefore, in the scenario, for the analysis of price and fuel efficiency, accessibility to charging stations was set as 3%, which is the same level as in the current market. The analysis result is illustrated in Figure 11. Provided the number of charging stations remains as it is, if 4 million KRW were provided in subsidy at the time of purchase of electric vehicles and the battery had a mileage of 30 km/*l*, then the net utility of electric vehicles would be positive at the rate of 33.3%. This is close to the target of the Korean government (of allowing electric vehicles to account for 30% of new vehicles in the market).

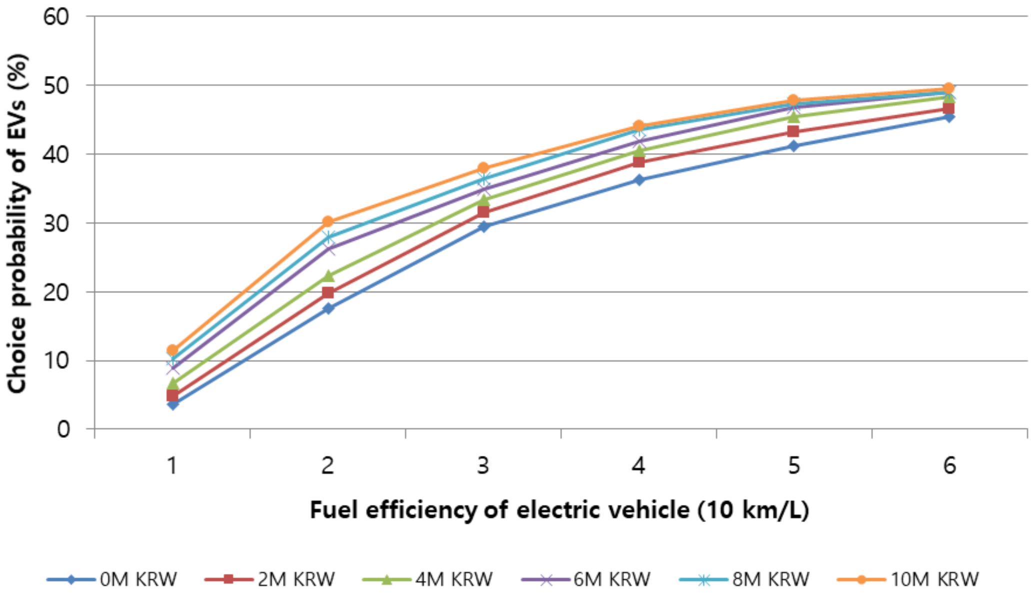

Figure 11. Choice Probability of EVs Based on Fuel Efficiency and Subsidy

Next, the result of scenario analysis, with subsidy, charging infrastructure, SUV, and fuel efficiency combined, is shown in Figure 12. The analysis result revealed that in the case of no subsidy, 30 km/*l* mileage, and accessibility at the current level of 3%, the net utility of electric vehicles would be positive at the rate of 29.4%. Meanwhile, when subsidy and mileage were the same (no subsidy and 30 km/*l* mileage) but accessibility to charging stations was 60%, the net utility of electric vehicles would be positive at the rate of 40.2%. However, the goal of the Korean government is to achieve 25% accessibility of charging stations to that of gas stations by the year 2020. This requires intensive investment in building additional charging stations, even if the subsidy for electric vehicles cannot be maintained. If this is not practical, it would be better to invest first in regions and places frequented by consumers interested in electric vehicles in order to accelerate the pace of diffusion. Furthermore, the results reveal that providing SUV options has a similar effect on promoting the purchase of electric vehicles. In summary, corporations and the government should come up with a comprehensive set of plans to support and encourage the diffusion of electric vehicles. To achieve this, corporations should focus on developing electric SUVs, while the government should concentrate its efforts on enhancing the charging infrastructure.

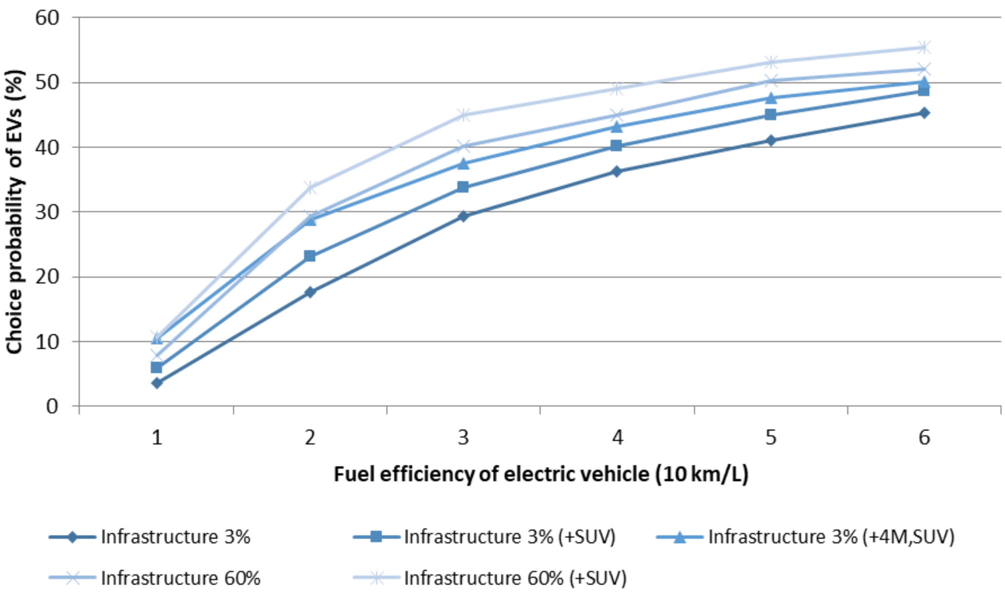

Figure 12. Choice Probability of Electric Vehicles Based on Fuel Efficiency, Subsidy, Infrastructure, and Provision of SUVs

4.4.4 Conclusion and Implications

Even if a new product is released in the market, consumers tend to buy the new product based on the attributes of the product they currently have when the new product serves as a substitute for the existing one. Therefore, when incorporating the reference-dependent preferences into the discrete choice model, asymmetric preferences for a variety of attributes can be analyzed, and the results can be applied to build a successful diffusion strategy for new products in the market. Unfortunately, there has no study has yet analyzed consumer preferences for vehicles using the reference-dependent choice model. This is because the existing reference-dependent choice model is limited in its application, as it cannot be applied to attributes for which the preferred direction is different, such as brand and vehicle types. Against this backdrop, this study divided vehicle attributes into those with the same preference direction and those with different preference directions, and analyzed consumers' asymmetric preferences using the reference-dependent choice model based on consistency, with the attributes of the vehicles that respondents currently possess as the reference points.

The estimation result using the proposed model revealed that the loss aversion parameters for vehicle type for which the preferred direction is different and accessibility to charging stations for which the preferred direction is the same were larger than 1. This implies that vehicle type and accessibility to charging stations are crucial in consumers' vehicle choice process. Therefore, even if electric vehicles have advantages over other types of vehicles in many respects, an electric sedan would greatly reduce the utility of consumers who possess and prefer SUVs. In this regard, asymmetric preferences for vehicle types have significant implications in South Korea's automobile market. The types of electric vehicles produced until 2018 were limited to compact, small, and medium-sized passenger cars. If a corporation considers the production of electric SUVs, it is expected to further increase the purchase probability of electric vehicles. Therefore, manufacturers of electric vehicles should consider the production of SUVs powered by electricity, while the government should implement policies to aid the production of electric SUVs to promote the diffusion of electric vehicles.

The scenario analysis shows that government policy should focus on increasing the number of charging stations to close to the number of gas stations to promote the purchase of electric vehicles. Even if the number of charging stations is not identical, the electric vehicle's share in the market would grow quickly if charging infrastructure were established to make it easier for consumers to charge their electric vehicles. However, accessibility to charging stations is a factor mainly determined by government policy, which is changing regularly. To encourage the diffusion of electric vehicles, it is important to establish a continuous and consistent policy for the predictable diffusion of electric vehicles, as various factors affecting consumer utility, such as power generation, charging infrastructure, and subsidies, depends on government policy. However, since it is beyond the scope of the present study to analyze how uncertainties of government policy influence consumers' marginal utility, this remains for future study.

There are other limitations of this study. First, the major attributes of electric vehicles were limited to six in this study in order to construct virtual alternatives. However, since there are attributes other than those suggested in this study, there limitation cannot entirely reflect consumer preferences. Next, for a more accurate comparison between internal combustion vehicles and electric vehicles, fuel efficiency should be calculated based on more precise information about charging fees and oil prices, but as this is beyond the scope of this study, the data were borrowed from the results of previous studies. This study focused on the analysis of consumer preferences for electric vehicles and a strategy for the diffusion of electric vehicles. However, a reduction in GHG emissions according to the spread of electric vehicles could be influenced by energy mix and driving patterns, and there is room for change in government policy based on the degree of reduction in GHG emissions. Thus, future study would greatly benefit from analyzing the government's support policy for electric vehicles, used as a tool for GHG emissions reduction, and the level of the government's reduction target from the perspective of consistency.

4.5 Empirical Study 3: Telemedicine Market of Health Field

4.5.1 Introduction

With the continuous advancements in the information and communication technology industry, the incorporation of telecommunication technologies into the healthcare sector has given birth to telemedicine. Although there are many different definitions of telemedicine, they are essentially similar; telemedicine refers to the activity of exchanging medical information and providing medical service using telecommunication technology. The most important advantage of telemedicine is the elimination of the temporal and spatial distance between the provider and receiver of the service (Park, Chon, Lee, Choi, & Yoon, 2011).

In South Korea, the national health insurance allows patients to have access to medical services at relatively affordable costs (Park et al., 2011). Against this backdrop, patients tend to prefer and use big hospitals, such as university hospitals, and it is not rare for patients to wait for a long time to see a doctor and for as long as several months to have a surgery (Park et al., 2011). It is expected that telemedicine service would greatly improve the quality of patient experience in terms of diagnosis and treatment, if relatively simple medical services, such as the diagnosis of certain diseases or issuing of prescriptions, could be provided through telemedicine (Park et al., 2011).

This study aimed to identify strategies required for the successful introduction of innovative telemedicine. To do this, it was necessary to conduct an analysis of potential consumers' preferences for telemedicine. Within this context, the objective of this study was to use the discrete choice model to analyze consumer preferences for telemedicine service. The reference-dependent choice model was used to overcome the limitations of a symmetric model, including biased estimates for welfare, and to establish an asymmetric model. At the same time, potential consumers' asymmetric preferences for telemedicine service were analyzed more accurately by using the advanced reference-dependent choice model, which incorporates the reference points shifting rule.

4.5.2 Survey Data

This study was conducted through questionnaires, and data were collected from 350 people aged 20–59 years, residing in Seoul and other major cities[8] in South Korea, from July to August 2017. The survey method used in this study is a discrete choice experiment. A discrete choice experiment, in which respondents are presented with a set of alternatives consisting of the key attributes of telemedicine services, similar to the actual selection environment, is a suitable method for a consumer preference analysis in South Korea, where telemedicine services are still not active. The questionnaire survey was conducted by Gallup Korea, a member of the global polling organization, through face-to-face interviews, and the interviewees were selected using a quota sampling method. The demographic characteristics of the respondents of this survey are summarized in Table 21.

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[8] Gyoenggi (New towns) and five major cities (Busan, Incheon, Daegu, Daejeon, and Gwangju)

Table 21. Demographic Characteristics of the Telemedicine Survey Respondents

Group		No. of respondents (%)
Gender	Male	176 (50.3%)
	Female	174 (49.37)
Age	< 30	79 (22.6%)
	30–39	85 (24.3%)
	40–49	95 (27.1%)
	50–59	91 (26.0%)
Average monthly household income	3 million KRW or less	39 (11.1%)
	3 to 3.9 million KRW	73 (20.9%)
	4 to 4.9 million KRW	108 (30.9%)
	5 million KRW or more	130 (37.1%)
Residing in	Seoul	139 (39.7%)
	Busan	46 (13.1%)
	Incheon	42 (12.0%)
	Daegu	33 (9.4%)
	Daejeon	30 (8.6%)
	Gwangju	30 (8.6%)
	Gyeonggi (New towns)	30 (8.6%)

In this study, six attributes were selected based on previous research on the analysis of consumer preferences for telemedicine services (Park et al., 2011). Other than the major functional attributes, non-functional attributes influencing the spread of telemedicine, such as regulations on telemedicine information, were included as attributes of the discrete choice experiment. Attributes of telemedicine alternative and the descriptions and levels of attributes are summarized in Table 22.

Table 22. Description and Levels of Attributes of Telemedicine Service Alternatives

Attributes	Description	Levels
Monthly service charge	Monthly charge for the telemedicine service provided through computers or mobile devices	10,000 KRW/month 20,000 KRW/month 30,000 KRW/month
Medical treatment cost compared to face-to-face treatment	Relative cost of telemedicine service for one session, compared to face-to-face visits	10% lower than face-to-face service 30% lower than face-to-face service 50% lower than face-to-face service
Response time	The amount of time that is required for the system to respond to the request of the telemedicine service	Immediately Within 6 hours Within 12 hours
Scope of service	Range of services provided by telemedicine technology	Diagnosis of diseases and consultation Diagnosis of diseases and consultation + treatment and giving prescriptions
Regulations on telemedicine information	The scope of information protected by the Personal Information Protection Act in the process of using patients' medical information	Patients' consent required at all stages (Very high level of regulation) Patients' consent required at certain stages (High level of regulation)
Service providers	Hospitals where telemedicine services are available. Divided into general and private hospitals.	General hospital + private hospital Private hospital

In this study, a total of 15 alternative cards were selected through orthogonal design, which is fractional factorial design, of the alternatives that can be created by mixing the telemedicine attributes and the levels of each attribute presented in Table 22. Subsequently, the 15 cards were grouped into five choice sets consisting of three cards each. Furthermore, a no-choice alternative was included in each choice set (Ahtiainen, Pouta, & Artell, 2015). Status quo alternatives without additional cost are referred to as “no choice” or “current state.” The no-choice alternative was included to represent the real choice situation and prevent the respondents from making a forced choice, in addition to deriving consistent welfare estimates (Batsell & Louviere, 1991). In the study of the marketing field in Section 4.3 and of the energy field in Section 4.4, alternatives were set for smartphones and vehicles, respectively. In these cases, analysis was conducted with respondents who possessed a smartphones and vehicles, respectively. However, in the present case, there is no respondent who currently uses telemedicine service in South Korea, and thus, the analysis focused on acceptance of the service. Therefore, this study considered the no-choice alternative in the discrete choice experiment on telemedicine service. An example of the choice sets used in this study is presented in Table 23 (for all choice sets, refer to Appendix C).

Table 23. A Choice Set Example in the Discrete Choice Experiment of Telemedicine

Attribute	Type A	Type B	Type C	No Choice
Service charge	30,000 KRW/month	20,000 KRW/month	30,000 KRW/month	Use current face-to-face treatment services
Medical treatment cost	50% lower than face-to-face service	10% lower than face-to-face service	10% lower than face-to-face service	
Response time	Within 12 hours	Within 12 hours	Immediately	
Scope of service	Treatment and prescriptions	Diagnosis and consultation	Diagnosis and consultation	
Regulations on information	Consent required at certain stages	Consent required at all stages	Consent required at certain stages	
Service providers	General hospital + private hospital	Private hospital	General hospital + private hospital	
Choice	Type A	Type B	Type C	No-Choice

It is important to set reference points in the process of considering reference-dependent preferences. A reference point can be set as the current state, future expectation, or past experience. The reflection of the current state, which is widely used, means that the level of attributes of the product or service that the respondents currently have or use, is set as a reference point. However, since no respondent currently uses telemedicine service in South Korea, there is a limitation on using the current state as a reference point. According to existing studies on reference points, expectation can determine a reference point when the current state and expectation are different (Abeler, Falk, Goette, & Huffman, 2011; Kőszegi and Rabin, 2006; Marzilli et al., 2011). Thus, future expectations were set as reference points in this study. Specifically, to set a reference point influencing individual respondents' telemedicine service choice, an additional questionnaire was administered to obtain answers about the respondents' minimum expectation for each attribute. The details of the questionnaire are summarized in Table 24.

Table 24. Minimum Expectation Level for the Attributes of Telemedicine Service

Attribute	Minimum expectation level
Monthly service charge (respond in Korean won amounts)	( ) 1,000 KRW/month
Medical treatment cost compared to face-to-face treatment (respond using percentage)	( )% lower than face-to-face treatment
Response time (respond using hours of time)	Respond within ( ) hours (0 for immediate response)

4.5.3 Estimation Results and Discussion

This study analyzed potential consumers' preference for the attributes of telemedicine service using the standard mixed logit model. The result is presented in Table 25 as S-Model. The analysis result revealed that on average, consumers prefer the service when its monthly charge is lower, medical treatment cost compared to face-to-face treatment is lower, response time is shorter, and there are bigger and more kinds of service providers. However, the scope of service and the level of telemedicine information regulation do not have statistically significant effects.

Next, the result of the analysis incorporating the respondents' expectations as reference points into the existing reference-dependent choice model is presented in Table 25 as R-Model-B. In this model, the telemedicine service alternative consists of the attributes assumed to be in the same preference direction among consumers, and it is not necessary to use the reference-dependent choice model based on consistency proposed in this study. The analysis result showed that the three dummy variables, not considering reference-dependent preferences, were similar to those of the estimation result in S-Model. The parameter estimates for the three linear variable levels in the preference and non-preference domains showed that the parameter in the non-preference domain was larger than that in the preference domain, following existing studies. As can be seen in the AIC and BIC statistics in Table 25, the existing reference-dependent choice model had a better fit than the mixed logit model.

Table 25. Estimation Results for the Telemedicine Attributes Using Existing Choice Models

Variables		S-Model	R-Model-B
Service charge (10,000 KRW/month)		-2.639***	
	Preference		1.630***
	Non-preference		-3.746***
Medical treatment cost compared to face-to-face		0.441***	
treatment (100%)	Preference		0.399**
	Non-preference		-0.527***
Response time (10 hours)		-0.337***	
	Preference		0.001
	Non-preference		-0.454***
Scope of service (Diagnosis, consultation, treatment, and prescriptions)		0.456	0.470
Regulations on telemedicine information (Patients' consent required at all stages)		0.323	0.421
Service providers (General hospital + private hospital)		1.745***	2.086***
No choice		-9.059***	-9.675***
Log-liklihood		-1889.2810	-1863.8462
AIC		3792.5620	3747.6924
BIC		3830.8336	3786.2717

***Significant at the 1% level, **Significant at the 5% level, *Significant at the 10% level

In addition, the loss aversion parameters for each attribute considering reference-dependent preferences, and the existence of asymmetric preferences were validated. The result is presented in Table 26. The analysis result revealed that the loss aversion parameters of the respondents were larger than 1 for such attributes as monthly service charge, medical treatment cost compared to face-to-face treatment, and response time, and that the respondents had asymmetric preferences. In particular, the loss aversion parameter for response time was significantly larger than those of other attributes, which implies that response time was highly likely to influence the choice of telemedicine service.

Table 26. Loss Aversion Parameters and Verification of Asymmetry

Variables	Loss Aversion Parameter	T-test Statistics	Preference
Monthly service charge	1.710	18.078	Asymmetry
Medical treatment cost compared to face-to-face treatment	1.070	2.796	Asymmetry
Response time	5.355	35.393	Asymmetry

Next, the MWTA and MWTP for the attributes of telemedicine service were investigated, and an analysis was conducted to observe whether there was asymmetry between the MWTA and MWTP. The result is presented in Table 27. In S-Model, a symmetric model, when the response time changed by 10 hours, the MWTP for improvement and the MWTA for worsening are same (9,585 KRW). By contrast, in the asymmetric R-Model-B, the MWTP for improvement is 2,140 KRW, while the MWTA for worsening is 18,675 KRW, showing a high level of asymmetry. Therefore, a symmetric model is subject to overestimation for improvement and underestimation for worsening, resulting in biased estimation. As for the attributes without considering reference points, the MWTP showed similar results in the two models. In particular, it was found that the MWTP for the regulation of telemedicine information is relatively smaller than that for other attributes. This means that Korean consumers are less sensitive to information regulation in telemedicine service.

Table 27. MWTA and MWTP for the Attributes of Telemedicine Service

Attribute	S-Model	R-Model-B	
	MWTP(=MWTA)	MWTP	MWTA
Medical treatment cost compared to face-to-face treatment (100%)	13,295 won	9,185 won	19,193 won
Response time (10 hours)	9,585 won	2,140 won	18,675 won
Scope of service	2,671 won	2,648 won	
Regulations on telemedicine information	1,635 won	1,258 won	
Service providers	5,530 won	4,363 won	

Then, consumers' asymmetric preferences for the attributes of telemedicine service were examined using the advanced reference-dependent choice model incorporating the reference points shifting rule. The result is presented in Table 28. The result of considering the attribute with the highest importance of loss aversion is represented as R-Model-S1. In R-Model-S2, the attributes with the importance of first and second highest loss aversion were considered. As the number of parameters in the model with the reference points shifting rule is not different from that of R-Model-B, log-likelihood values were used to compare the goodness-of-fit of the models. According to the comparison, the model fit of R-Model-S1 and R-Model-S2 improved by 4.6% and 4.9%, respectively, compared to R-Model-B. In summary, model fit was the best when reference points were shifted using the loss aversion importance of the two attributes out of the three attributes considering reference points.

Table 28. Estimation Results in the Advanced Reference-Dependent Choice Model

Variables		R-Model-S1	R-Model-S2
Service charge (10,000 KRW/month)	Preference	1.583***	1.454***
	Non-preference	-1.652***	-1.643***
Medical treatment cost compared to face-to-face treatment (100%)	Preference	3.114***	4.673***
	Non-preference	-3.039***	-2.545***
Response time (10 hours)	Preference	1.656***	1.349***
	Non-preference	-2.272***	-2.211***
Scope of service (Diagnosis, consultation, treatment, and prescriptions)		0.921***	0.956***
Regulations on telemedicine information (Patients' consent required at all stages)		0.669***	0.597***
Service providers (General hospital + private hospital)		1.166***	1.193***
No choice		-5.338***	-5.424***
Log-likelihood		-1778.3276	-1771.8536

***Significant at the 1% level, **Significant at the 5% level, *Significant at the 10% level

It is realistic to set the initial point of innovation, which can be created from the mix of attribute levels of telemedicine service, as the inferior level for each attribute. In the present study, the initial point was 30,000 KRW for the monthly service fee, 10% reduction in the cost compared to face-to-face treatment, and 12 hours of response time. The scope of the service was limited to the diagnosis of diseases and consultation, information regulation was set to high level of regulation, and the service provider was set as a private hospital. The probability of choosing “initial point” and “no choice” was 66.9% and 33.1%, respectively, in S-Model. Furthermore, the probability of choosing telemedicine service with such “initial point” and “no choice” was 60.7% and 39.3%, respectively, in R-Model-S2. This difference results from the underestimation of the marginal utility of the respondents for non-preference by the symmetric discrete choice model, compared to the asymmetric reference-dependent choice model when the initial point is inferior to that of respondents’ expectations. It can be concluded that R-Model-S2 can overcome the biased estimation result of S-Model without deriving excessive acceptance results.

Therefore, R-Model-S2, an asymmetric and unbiased model with the best model fit, was used to discuss strategies required for the diffusion of telemedicine services in this study. If potential consumers’ expectation level for telemedicine services falls, the probability of choosing the initial point increases, as represented by the blue line in Figure 13. However, it is difficult to shift expectations of the respondents; rather, it is more realistic to make the respondents evaluate the status quo with their expectations as a reference point. In this case, it takes more cost to maintain the status quo than using telemedicine service. In the case in which the level of innovative technology is the default level, the probability of choosing the initial point was 69.8%, as represented by red line in Figure 13. This result can be applied as a strategy to enhance the probability of acceptance, which is more effective than falling consumer expectation of 25%.

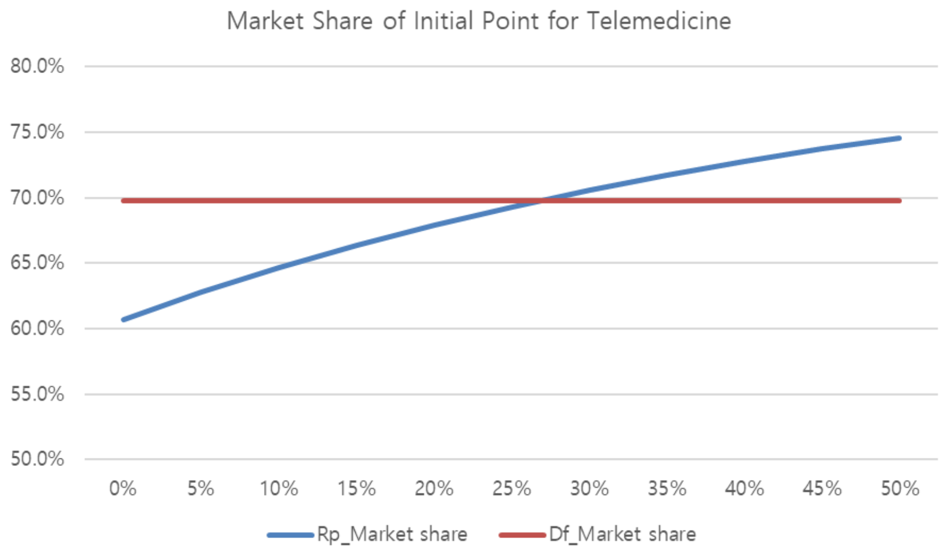

Figure 13. Choice Probability of the Initial Technology of Telemedicine by Strategy

4.5.4 Conclusion and Implications

The telemedicine system is an important component of the national health information infrastructure (Djamasbi, Fruhling, & Loiacono, 2009). Since a system that cannot be accepted easily by its consumers is less likely to be used effectively (Keil, Beranek, & Konsynski, 1995), it is necessary to carefully analyze potential consumers' preferences. In other words, it is important to design telemedicine based on consumer preferences for the successful introduction of the innovative service.

This study analyzed potential consumers' preferences for telemedicine service using the standard discrete choice model, the existing reference-dependent choice model, and the advanced reference-dependent choice model. According to the analysis result, the existing reference-dependent choice model and the advanced reference-dependent choice model suggested in this study produced unbiased estimation values compared to the discrete choice model, and also had improved goodness-of-fit. The results revealed that potential consumers have asymmetric preferences for the major attributes of telemedicine service, and the importance of loss aversion was the highest for response time. At the same time, this study explored a set of strategies required for the successful introduction of telemedicine service. The analysis result showed that the setting of default for innovative technology has a significant influence on the choice probability of the consumers.

In addition, a strategy exists to set up intermediate alternatives, which act to shift the reference point in the direction of the target alternative (Paolacci, Burson, & Rick, 2011). Accordingly, setting an intermediate alternative helps reduce perceived loss compared with the target alternative (Paolacci et al., 2011). In other words, even if an intermediate alternative is not adopted, the extent to which one treats their expectation level as a reference point is weakened, and the acceptance level can be heightened (Paolacci et al., 2011). Simultaneously, there have been experiments on the effect of personalized feedback, such as customized information, on the shifting of reference points (Abrahamse, Steg, Vlek, & Rothengatter, 2007; Carrico & Riemer, 2011). Against this backdrop, future study would greatly benefit from analyzing how various types of information influence reference points, such as the expectations of consumers.

Chapter 5. Summary and Conclusion

5.1 Concluding Remarks and Contributions

The standard economic model, based on the consumer utility theory of neoclassical economics, has been positioned as a dominant theory in modern economics. In particular, the discrete choice model, used for the analysis of consumer choice, is widely applied in adjacent fields as well as in economics, and its usefulness has been recognized. However, conventional standard economic models, including the discrete choice model, presuppose the perfect rationality of consumers and give only limited explanation about the anomalous behavior of consumers observed in real choice situations. A variety of theories have attempted to explain such bounded rationality of the consumer, including heuristics of cognitive psychology. Heuristics are classified into four groups, out of which the reference point and context effect have been found to significantly affect the behavior and choice of consumers.

Consequently, choice models in behavioral economics, which incorporate theories of cognitive psychology, such as heuristics, into the standard choice model of neoclassical consumer theory, are attracting increasing attention. In particular, the reference point effect is a key element of prospect theory, which is widely used to examine consumer behavior. Furthermore, prospect theory has developed into a reference-dependence theory, which considers the reference dependence for multiple attributes in a riskless choice situation. Since the reference-dependent theory and the discrete choice model can consistently explain the tradeoffs between multi-attributes and utility maximization, a reference-dependent choice model, incorporating reference-dependent theory into the discrete choice model, has been developed. This model has the advantage of explaining universal economic phenomena caused by loss aversion, such as the endowment effect and the status quo effect.

However, the existing reference-dependent choice model divides the relative levels of attributes, which is a difference between the attribute level of the alternative and reference points, simply into a gains domain and a losses domain to examine the consumer’s asymmetric preferences for each attribute. This results in an inconsistent definition of loss for the attribute when the attributes for which the preferred direction is different are analyzed using the existing reference-dependent choice model. In other words, the model has limitations, as it may produce a result inconsistent with the definition of loss aversion and asymmetric preferences explained by the reference point effect. Consequently, a wide range of empirical studies using the existing reference-dependent choice model focus only on the attributes for which the preferred direction is the same among consumers. Therefore, it is necessary to develop a reference-dependent choice model, which captures preference heterogeneity and considers the preferred directions as well as the relative level of attributes, in order to consider consistent reference-dependent preferences. Therefore, this study proposed a reference-dependent choice model based on consistency, which allows realistic behavior through preference heterogeneity and the preferred directions of consumers.

Another characteristic and limitation of the existing reference-dependent choice model, other than its simple dichotomous approach to the level of attributes, is the fact that reference points are fixed. Behavioral economics is significant, as it reflects the reality of consumers' behavior by including heuristics in the standard economic model, but its choice models are limited, as they independently include major heuristics, such as the reference point effect and the context effect, thereby only partly reflecting reality. Since the loss aversion effect, explained by the reference point effect, is a special kind of context effect, the reference point effect is strongly correlated with the context effect. Moreover, although there are potential reasons for reference points to shift according to the choice context, no study considers the shifting of reference points in the reference-dependent choice model using data from the discrete choice experiment. Therefore, this study proposed the reference points shifting rule based on the major decision strategies, explaining the context effect. Subsequently, an advanced reference-dependent choice model was proposed by integrating the reference points shifting rule into the reference-dependent choice model based on consistency first proposed in this study.

As a result, the methods proposed in this study extensively reflect the reality of the choice environment and the behavior of the consumer. The proof of the appropriate consideration of behavioral reality lies in the excellence of the model fit compared to existing choice models. For this reason, the methods in this study were applied in empirical studies in areas in which economic models are mostly used for the analysis of consumer preferences, such as marketing, energy, and healthcare. Consumer preferences were analyzed for the smartphone market (marketing), vehicle market (energy), and telemedicine (healthcare). The analysis results showed that the reference-dependent choice model based on consistency proposed by this study has better goodness-of-fit than the standard discrete choice model and the existing reference-dependent choice model. In addition, the more advanced reference-dependent choice model, which includes the reference points shifting rule for the loss aversion and the context effect, was found to have a better model fit than the reference-dependent choice model based on consistency.

The results of the empirical studies, other than the model fit, can be summarized as follows. First, the attributes for which the preferred direction among consumers is different have larger influence on their utility than those for which the preferred direction is the same. Second, when the asymmetric preferences of the consumer are analyzed for the attributes for which the preferred direction is different using the existing reference-dependent choice model, it might not be consistent with the economic definitions related to loss aversion and might fail to produce statistically significant estimation. Third, the analysis using the proposed reference-dependent choice models revealed that the consumer’s preferences for all attributes are asymmetrical, while there are some attributes with loss aversion parameters smaller than 1, although the parameters for most attributes are larger than 1. Therefore, it cannot be generalized that loss aversion parameters are larger than 1. Fourth, according to the analysis result using the reference-dependent choice models proposed in this study, the ratio of MWTA to MWTP was larger than 1 for all attributes and MWTA and MWTP were asymmetrical. However, the incorporation of the reference points shifting rule changed the loss aversion parameters, and in turn influenced the ratio of MWTA to MWTP. If the ratio was overestimated when using the reference-dependent choice model based on consistency, it could be relaxed by considering the reference points shifting rule.

The implications of this study can be summarized as follows. First, this study suggested new methods related to studies on consumer choice. These methods are more refined and valid for the analysis of consumer preferences and demand prediction than existing methods. Second, this study verified the results of major theories and empirical studies related to reference dependence and loss aversion. Third, this study discussed main topics related to reference dependence and loss aversion in adjacent areas of economics and proposed applicable methods.

5.2 Limitations and Future Studies

The strength of the reference-dependent choice model based on consistency, one of the methods proposed in the current study, lies in its ability to estimate the asymmetric preferences of the consumer on all attributes of alternatives, which is consistent with the definition of loss aversion regardless of preferred directions. However, in the proposed reference-dependent choice models, care is required during the interpretation of the estimation result and scenario analysis because each of the relative levels of attributes, for which the preferred direction of the consumer is different, is grouped into two types, preference domain and non-preference domain. In addition, similar to the methods of general behavioral economics, an empirical application of the methods presented in this study is not simple in that it requires a separate computer language and the writing of statistical program codes.

Among the methods proposed in this study, the advanced reference-dependent choice model, which considers the reference points shifting rule, has the advantage of abundantly reflecting the reality of behavior considering the context effect as well as the reference point effect among the heuristics. The limitation, however, is that whether or not the shifted reference points are actually those that have the most influence on the actual choice and utility of the consumer can be validated only indirectly through such means as a comparison of goodness-of-fit tests. This is because there is no consensus among previous studies on the formation of reference points. Accordingly, in the future research, the principle of the formation of reference points in a multi-attribute space will be investigated and the factors that affect the formation of reference points will be closely investigated using such variables as demographic and psychographic characteristics. In addition, the reference points shifting rule proposed in this study is an appropriate method for multiple attributes. In other words, it is an appropriate method for preference analysis of durable goods and high technology products that have relatively complex attributes of alternatives. Therefore, the rule for reference points shifting needs to be set up differently from the rule presented in this study for preference analysis of consumers of non-durable goods, which consists of a small number of relatively simple but important attributes.

In the reference-dependent choice models proposed in this study, it is assumed that consumers trade-off the relative levels classified through the preferred directions and reference points of each attribute to evaluate alternatives of a choice set. However, there may be claims that some decision strategies of the context effect consider some attributes only when consumers face complex or familiar situations. As such, when a non-compensatory decision rule is reflected in the models, the existing random utility framework cannot be simply applied. Accordingly, the reference-dependent behavior of consumers using only some attributes of alternatives will be modeled in future research.

Existing studies that consider the reference effect focus on investigating the loss aversion effect and asymmetric preferences. In addition, the hierarchical Bayesian logit model of Section 2.1.3 can be used to closely analyze factors that affect loss aversion parameters. Specifically, Kim et al. (2018) classified the relative levels into a preference domain and a non-preference domain regarding the changes in the power generation share of renewable energy. The result indicated that the absolute value of the estimated parameter for non-preference domain was larger than the estimated parameter for preference domain. In other words, the parameter for the non-preference domain representing the case in which the public preferred renewable energy while the share of renewable energy decreased, and that in which public did not prefer renewable energy while the share of renewable energy increased was larger than the parameter for the preference domain representing the opposite case. Since the loss aversion parameter was found to be larger than 1, the factors affecting the degree of non-preferrence for the changes in the power generation share of renewable energy were additionally analyzed. Furthermore, it was found that the higher is the satisfaction with the current power service, the higher is the degree of non-preference for the change in the power generation share of renewable energy. Thus, the thorough identification of factors that affect loss aversion and asymmetric preference provides meaningful information to government policymakers and corporate marketers. Accordingly, the factors that affect the degree of loss aversion will be investigated multilaterally in future research by expanding empirical studies carried out in the present study.

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Appendix A: Survey Questionnaires for Smartphones

A-1 Choice Set in the Discrete Choice Experiment of Smartphones

Table A-1-1. First Choice Set in the Discrete Choice Experiment of Smartphones

Attribute	Type A	Type B	Type C	Type D
Brand	Other	LG	Apple	Samsung
Screen Size	4.5 inches	4.5 inches	6.5 inches	5.5 inches
Storage Capacity	256 GB	128 GB	32 GB	128 GB
Recognition Technology	Yes	No	Yes	Yes
Purchase Price	300,000 KRW	650,000 KRW	300,000 KRW	300,000 KRW
Choice	Type A	Type B	Type C	Type D

Table A-1-2. Second Choice Set in the Discrete Choice Experiment of Smartphones

Attribute	Type A	Type B	Type C	Type D
Brand	Other	LG	Apple	Samsung
Screen Size	6.5 inches	6.5 inches	4.5 inches	5.5 inches
Storage Capacity	64 GB	32 GB	32 GB	64 GB
Recognition Technology	No	Yes	No	No
Purchase Price	1,000,000 KRW	650,000 KRW	650,000 KRW	650,000 KRW
Choice	Type A	Type B	Type C	Type D

Table A-1-3. Third Choice Set in the Discrete Choice Experiment of Smartphones

Attribute	Type A	Type B	Type C	Type D
Brand	Other	LG	Apple	Samsung
Screen Size	6.5 inches	4.5 inches	5.5 inches	4.5 inches
Storage Capacity	256 GB	64 GB	64 GB	256 GB
Recognition Technology	No	Yes	No	Yes
Purchase Price	650,000 KRW	300,000 KRW	300,000 KRW	1,350,000 KRW
Choice	Type A	Type B	Type C	Type D

Table A-1-4. Choice Set 4 in the Discrete Choice Experiment of Smartphones

Attribute	Type A	Type B	Type C	Type D
Brand	Other	LG	Apple	Samsung
Screen Size	5.5 inches	4.5 inches	4.5 inches	6.5 inches
Storage Capacity	32 GB	128 GB	128 GB	64 GB
Recognition Technology	Yes	No	No	No
Purchase Price	1,000,000 KRW	1,350,000 KRW	1,000,000 KRW	1,350,000 KRW
Choice	Type A	Type B	Type C	Type D

A-2 Survey Questionnaires for Peer Effect Analysis

The following questions (2–5) used a 5-point Likert scale.

1) Which smartphone brand do you and your peers own?

   (1) Samsung, (2) LG, (3) Apple, (4) Huawei (or Xiaomi), (5) Motorola (or blackberry), (6) Others

2) How satisfied are you and your peers with the manufacturers of the smartphone you/they possess?

3) How much expertise do you and your peers have about smart devices?

4) How much are you and your peers interested in new products?

5) To what extent do your peers advise you when you purchase high-tech products?

Table A-2-1. Survey Questionnaire for Peer Effect Analysis

Div.	Question 1)	Question 2)	Question 3)	Question 4)	Question 5)
Respondent					
Peer 1					
Peer 2					
Peer 3					
Peer 4					
Peer 5					

Appendix B: Survey Questionnaires for Vehicles

Table B-1. First Choice Set in the Discrete Choice Experiment of Vehicles

Attribute	Type A	Type B	Type C	Type D
Fuel type	Gasoline	Diesel	Hybrid	Electricity
Vehicle type	Sedan	SUV(RV)	SUV(RV)	Sedan
Fuel efficiency	40 km/*l*	40 km/*l*	20 km/*l*	20 km/*l*
Vehicle price	25 million KRW	40 million KRW	40 million KRW	35 million KRW
Accessibility	50%	80%	50%	100%
Smart car options	No	Yes	Yes	No
Choice	Type A	Type B	Type C	Type D

Table B-2. Second Choice Set in the Discrete Choice Experiment of Vehicles

Attribute	Type A	Type B	Type C	Type D
Fuel type	Gasoline	Diesel	Hybrid	Electricity
Vehicle type	Sedan	SUV(RV)	SUV(RV)	Sedan
Fuel efficiency	20 km/*l*	20 km/*l*	40 km/*l*	40 km/*l*
Vehicle price	35 million KRW	25 million KRW	35 million KRW	40 million KRW
Accessibility	50%	80%	50%	80%
Smart car options	Yes	No	No	Yes
Choice	Type A	Type B	Type C	Type D

Table B-3. Third Choice Set in the Discrete Choice Experiment of Vehicles

Attribute	Type A	Type B	Type C	Type D
Fuel type	Gasoline	Diesel	Hybrid	Electricity
Vehicle type	SUV(RV)	Sedan	Sedan	SUV(RV)
Fuel efficiency	40 km/*l*	10 km/*l*	10 km/*l*	40 km/*l*
Vehicle price	40 million KRW	40 million KRW	25 million KRW	25 million KRW
Accessibility	100%	50%	100%	50%
Smart car options	No	No	Yes	Yes
Choice	Type A	Type B	Type C	Type D

Table B-4. Choice Set 4 in the Discrete Choice Experiment of Vehicles

Attribute	Type A	Type B	Type C	Type D
Fuel type	Gasoline	Diesel	Hybrid	Electricity
Vehicle type	SUV(RV)	Sedan	Sedan	SUV(RV)
Fuel efficiency	10 km/*l*	40 km/*l*	40 km/*l*	10 km/*l*
Vehicle price	35 million KRW	35 million KRW	30 million KRW	30 million KRW
Accessibility	80%	50%	80%	50%
Smart car options	Yes	Yes	Yes	Yes
Choice	Type A	Type B	Type C	Type D

Appendix C: Survey Questionnaires for Telemedicine

Table C-1. First Choice Set in the Discete Choice Experiment of Telemedicine

Attribute	Type A	Type B	Type C	No Choice
Service charge	30,000 KRW/month	20,000 KRW/month	30,000 KRW/month	Use current face-to-face treatment services
Medical treatment cost	50% lower than face-to-face service	10% lower than face-to-face service	10% lower than face-to-face service	
Response time	Within 12 hours	Within 12 hours	Immediately	
Scope of service	Treatment and prescriptions	Diagnosis and consultation	Diagnosis and consultation	
Regulations on information	Consent required at certain stages	Consent required at all stages	Consent required at certain stages	
Service providers	General hospital + private hospital	Private hospital	General hospital + private hospital	
Choice	Type A	Type B	Type C	No Choice

Table C-2. Second Choice Set in the Discete Choice Experiment of Telemedicine

Attribute	Type A	Type B	Type C	No Choice
Service charge	30,000 KRW/month	10,000 KRW/month	10,000 KRW/month	Use Current face-to-face treatment services
Medical treatment cost	30% lower than face-to-face service	30% lower than face-to-face service	50% lower than face-to-face service	
Response time	Immediately	Immediately	Within 6 hours	
Scope of service	Diagnosis and consultation	Treatment and prescriptions	Diagnosis and consultation	
Regulations on information	Consent required at all stages	Consent required at certain stages	Consent required at all stages	
Service providers	Private hospital	Private hospital	General hospital + private hospital	
Choice	Type A	Type B	Type C	No Choice

Table C-3. Third Choice Set in the Discete Choice Experiment of Telemedicine

Attribute	Type A	Type B	Type C	No Choice
Service charge	20,000 KRW/month	10,000 KRW/month	10,000 KRW/month	Use Current face-to-face treatment services
Medical treatment cost	10% lower than face-to-face service	50% lower than face-to-face service	30% lower than face-to-face service	
Response time	Immediately	Immediately	Within 12 hours	
Scope of service	Treatment and prescriptions	Diagnosis and consultation	Treatment and prescriptions	
Regulations on information	Consent required at certain stages	Consent required at certain stages	Consent required at all stages	
Service providers	General hospital + private hospital	Private hospital	General hospital + private hospital	
Choice	Type A	Type B	Type C	No Choice

Table C-4. Fourth Choice Set in the Discete Choice Experiment of Telemedicine

Attribute	Type A	Type B	Type C	No Choice
Service charge	30,000 KRW/month	10,000 KRW/month	20,000 KRW/month	Use Current face-to-face treatment services
Medical treatment cost	10% lower than face-to-face service	10% lower than face-to-face service	30% lower than face-to-face service	
Response time	Within 6 hours	Within 12 hours	Within 6 hours	
Scope of service	Treatment and prescriptions	Diagnosis and consultation	Diagnosis and consultation	
Regulations on information	Consent required at all stages	Consent required at certain stages	Consent required at certain stages	
Service providers	Private hospital	Private hospital	General hospital + private hospital	
Choice	Type A	Type B	Type C	No Choice

Table C-5. Fifth Choice Set in the Discete Choice Experiment of Telemedicine

Attribute	Type A	Type B	Type C	No Choice
Service charge	10,000 KRW/month	20,000 KRW/month	10,000 KRW/month	Use Current face-to-face treatment services
Medical treatment cost	10% lower than face-to-face service	50% lower than face-to-face service	10% lower than face-to-face service	
Response time	Immediately	Immediately	Within 6 hours	
Scope of service	Diagnosis and consultation	Treatment and prescriptions	Treatment and prescriptions	
Regulations on information	Consent required at all stages	Consent required at all stages	Consent required at certain stages	
Service providers	General hospital + private hospital	Private hospital	Private hospital	
Choice	Type A	Type B	Type C	No Choice

Abstract (Korean)

소비자 선택을 분석하기 위해 널리 이용되고 있는 이산선택모형과 같은 표준 경제모형에서 응답자의 선호는 준거점과 무관한 것으로 가정되고 있다. 하지만, 실제 의사결정과정에서 소비자들은 대안의 절대적인 속성 수준이 아니라 준거점에 의존한 상대적인 속성 수준에 기반하여 제품 또는 서비스를 선택한다. 이와 같이 행동의 현실성을 고찰하는 인지심리학의 휴리스틱 이론 중에서 준거점 효과의 중요성이 강조됨에 따라, 심리경제학 및 행동경제학 분야의 소비자 연구들은 준거의존 선호를 일반적인 가정으로 인식해오고 있다. 이에 따라 이산선택모형에 준거의존 효용함수를 통합한 준거의존 선택모형이 개발되었다. 준거의존 선택모형은 표준경제모형에 손실회피 효과를 포함한 것으로 대안의 속성에 대한 소비자의 비대칭적 선호를 분석하는데 유용하게 이용되고 있다. 하지만 기존 준거의존 선택모형은 소비자들의 선호방향이 동일한 시간 및 비용과 같은 일부 속성들의 비대칭적 선호를 분석하는데 적합한 방법론이므로, 그 적용에 한계가 있는 실정이다. 기존 준거의존 선택모형을 이용하여 선호방향이 상이한 속성을 분석할 경우, 비대칭적 선호로 도출되는 손실회피 모수 및 MWTP 대비 MWTA의 비율 등은 경제학적 정의와 모순되는 결과물이다. 이에 따라, 본 연구의 첫번째 목적은 소비자의 선호방향이 상이한 속성들에 대해서도 준거의존 선호이론을 고려할 수 있는 무모순성을 지닌 준거의존 선택모형을 제안하는 것이다. 다음으로, 경제학의 소비자 연구들에 따르면 의

사결정자들은 손실을 회피하기 위해 보다 많은 노력을 기울이며, 대안을 구성하는 일부 속성을 중심으로 대안을 평가하는 맥락 효과가 나타나는 것으로 밝혀졌다. 따라서 소비자들은 손실회피 중요가 큰 속성들의 준거점을 만족하는 대안에 직면할 경우, 상대적으로 손실회피 중요도가 낮은 속성들의 준거점을 부정적인 방향으로 이동시킬 유인이 발생한다. 즉, 선택맥락의 관점에서 소비자들의 준거점은 이동될 가능성이 존재한다. 그럼에도 불구하고, 기존 준거의존 선택모형은 고정된 준거점 프레임에 의존하고 있으며, 이산선택모형에 준거점 효과와 맥락 효과를 통합한 연구는 전무한 실정이다. 따라서 본 논문의 두번째 목적은 우선 소비자들은 선호하지 않는 결과를 피하기 위해 보다 많은 노력을 기울인다는 점에 근거하여 손실회피의 상대적 중요도와 맥락 효과를 설명하는 결정전략 이론을 이용하여 준거점 이동 규칙을 제안하는 것이다. 그리고 무모순성을 기반으로 한 준거의존 선택모형에 준거점 이동 규칙을 통합하여 진보된 준거의존 선택모형을 제안하고자 한다. 진보된 준거의존 선택모형은 휴리스틱 이론 중 가장 중요하게 언급되는 준거점 효과와 맥락 효과를 통합적으로 포함하기 때문에 의사결정 과정의 현실성을 보다 풍부하게 반영하는 방법론이다. 이에 따라 본 논문에서 제시한 방법론은 실증 모형의 성과를 증가시키고, 소비자 행동에 대한 보다 깊은 이해를 제공 가능하다.

주요어 : 이산선택모형; 준거점 효과; 손실회피모수; 준거의존모형; 준거의존선호; 선택맥락 효과
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