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The Role of Antecedent Volition on Consumer Evaluative Processes and

Choice Behavior

by

Lianhua Li

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ABSTRACT

Antecedent volition, such as participation strategies, goals, mindsets and information processing modes, has been shown to influence consumer evaluative processes and choice in consumer behavior literature. However, these forms of pre-evaluation volition have been ignored in the quantitative modeling of consumer choice. Ignoring them may lead to inaccurate predictions and loss of insight into consumer behavior that might help formulate innovative marketing strategies. This thesis aims to explicitly incorporate antecedent volition into the modeling of consumer decision-making processes. Specifically, I focus on two forms of antecedent volition, participation strategy and goals. Accordingly, this thesis consists of two essays. The first essay examines the possibility that individuals first formulate a strategy on whether to engage in a decision (i.e., is this decision relevant to me?) prior to evaluating presented options. The second essay investigates, assuming volition to engage in a decision, situations in which multiple goals simultaneously guide evaluative processes. In each essay, a new choice model is developed that explicitly incorporates the corresponding form of antecedent volition (participation strategy or goals) into the model specification. Employing these models, I find empirical evidence that both forms of the antecedent volition not only influence but also are influenced by the evaluation of product assortment provided in decision context. It is also found that accounting for these forms of pre-evaluation volition is likely to produce more reliable predictions on Willingness To Pay for product attribute changes. Other managerial implications about allowing for these forms of antecedent volition are also discussed in the thesis, such as improving targeting, positioning and advertising strategies.

KEY WORDS: Antecedent Volition, Replacement Decision, Choice Behavior, Choice Set Formation, Prospect Theory, Durable Goods, Goals, Choice Model, Goal-based Choice, Context-dependent Choice

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1. INTRODUCTION

Previous marketing literature has documented an extensive discussion on the existence of certain volitional processes preceding evaluation and their effects on subsequent information processing. Among these prior volitional conditions are participation strategies, goals, mindset and information processing modes. For example, people may actively decide not to engage in a decision (i.e., formulating a no-participation strategy) when faced with new options, possibly due to the cost of thinking (Shugan 1980) and/or risk aversion (Fernandez and Rodrik 1991; Kahneman, Knetsch and Thaler 1991). Park and Smith (1989) have found that individuals, under certain circumstances, may have salient goals prior to a decision and thus engage in goal-directed top-down information processing. Studies conducted by Liu (2008) further suggest that this goal-directed top-down information processing causes people to be more likely to favor highly desirable but less feasible options. Additionally, construal level theory (see Trope and Liberman 2010) proposes that individuals might set up either a more abstract or concrete pre-decisional mindset that may in turn influence preferences. It has also been found that construal levels and goals are related in the sense that people who intend to achieve the goals of advancement and growth (promotion focus; see Higgins 2000) tend to have a more abstract mindset while those who intend to achieve the goals of safety and security (prevention focus; see Higgins 2000) tend to have a more concrete mindset (Lee, Keller and Sternthal 2010). Taken together, the above-mentioned studies suggest that individuals are not likely to arrive at a decision scenario with a blank mindset, but are likely to set up certain prior conditioning factors (e.g., participation strategies, goals, construal levels, information processing modes) which will affect evaluation of subsequent information presented in decision scenarios.

However, psychology and consumer behavior research treats such prior volitional conditions as outside decision-making processes by simply priming a certain mindset (e.g., goal or construal level) prior to a decision scenario; quantitative modeling of consumer choice generally overlooks possible roles of the prior volition. This thesis aims to incorporate prior volitional stages into a broader picture of decision-making by modeling a multi-stage process in which prior volitions are followed by evaluative processes conditional on these volitions. I focus on two forms of the above-mentioned antecedent volition, participation strategy and goals, in this thesis as they are critical to consumer decision-making. Specifically, the prior decision on whether to participate in decision-making significantly influences the subsequence choice consumers make; the activated goals prior to decision scenarios also greatly impact consumer behavior as goals drive consumer decision-making processes (Markman and Brendl 2000).

This thesis consists of two essays that investigate the above two forms of antecedent volition respectively. The first essay investigates the possibility that individuals make a higher-level decision on whether the decision is relevant to them before starting to evaluate presented alternatives. Specifically, in the context of replacement decisions for consumer durables, it is possible that when faced with a replacement opportunity, individuals first ask the question of “Shall I replace or not?” before evaluating new offers. Two replacement strategies might be formulated in this situation: a no replacement strategy (not considering new products at all) versus a replacement strategy (considering only new products). Such replacement strategies are expressed as choice set formation processes in the model since each strategy corresponds to a particular choice set. Conditional on those replacement strategies, a reference-dependent evaluative process, which uses the currently owned-product as a reference point, is modeled. By making evaluations reference-dependent (based on Prospect Theory, see Kahneman and Tversky 1979) but conditional on the selected replacement strategy, this essay leads to an enhanced understanding of replacement decisions.

The second essay assumes that decision makers have decided to engage in a decision, then examines whether individuals bring multiple predetermined goals to decisions and how those goals are attained through product selection. It should be noted that in the first essay involving durable replacement, multiple goals have not been accounted for. However, in the second essay multiple goals are allowed to be simultaneously active. It is likely that when multiple goals are present, individuals first engage in a goal weighting process in which resources (effort and time) are allocated across multiple goals. It is also likely that these prior goal weights are adjusted by the actual goal attainability of a choice scenario. This essay explicitly models the goal weighting and goal weight adaptation process and allows for product attributes to be evaluated with respect to goals in terms of their usefulness in goal attainment. Such a comprehensive modeling framework makes it possible to better reveal how multiple goals direct decision processes.

At a broad level, the contribution of this thesis is two-fold. First, this thesis provides a richer understanding about decision processes by treating the setup of prior volitional stages (i.e., strategies and goals) as a part of these processes. Specifically, it investigates the formulation of replacement strategies (i.e., whether to engage in a decision or not) and the use and weighting of multiple goals, and examines the interplay of those prior stages with subsequent evaluative processes. Both essays aim to provide a better understanding of human decision making by proposing a more comprehensive view of decision processes that envision decision makers as problem-solvers that decide "how to decide" as part of their choice process. Second, new statistical models are developed to describe these comprehensive decision processes in which multiple decision levels are involved. In these models, the prior stages are specified as higher-level actions, conditional on which product attributes are evaluated. It is shown that these new models, compared with the corresponding alternative models, have better model fit and may make more reliable policy predictions.

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2. DURABLE REPLACEMENT DECISIONS & THE INCUMBENT PRODUCT

This essay aims to incorporate participation strategy into consumer replacement decisions. Specifically, it proposes a new perspective on replacement decisions, in which consumers first form a replacement strategy (i.e., do I replace or not) and conditional on replacement, evaluate the new products and choose the best from them. This multi-stage perspective is fundamentally different from the conventional single-stage perspective on replacement decisions, in which consumers directly enter the evaluative process without forming any replacement strategies. That is, they start evaluating both the incumbent and new products when faced with a replacement opportunity, and then choose the best option among them, which may or may not lead to replacement. The key difference between the two perspectives lies in whether the special roles of the incumbent product are recognized. In the conventional perspective, the incumbent product is treated no differently from the new products. However, in the new one, the incumbent product serves as a pivotal option that determines the selection of replacement strategies. Stated differently, the incumbent product is not traded off with the new products in the evaluative process but directly influences the higher-level decision on whether to replace. I test this new perspective with a new choice model that characterizes the special roles of the incumbent product in replacement decisions. Besides the role of determining replacement strategies, I also account for other two important roles of the incumbent product: (a) serving as the reference point against which the new products are evaluated and (b) acting as a barrier to replacement by imposing mental cost on consumers.

2.1 INTRODUCTION

Replacement purchases play a significant role in driving the sales of consumer durables, especially for technology products, such as personal computers, mobile phones and digital cameras (Computer Industry Almanac Inc.2010; Gartner Inc.2008; InfoTrends 2007). In the existing quantitative research on durable replacement decisions, much attention has been directed toward investigating the timing of replacement (e.g., Gordon 2009; Rust 1987), which is certainly one of the key issues of replacement decisions. But the role of the incumbent (currently-owned) product in replacement decisions, another important aspect of replacement decisions, has been largely ignored in quantitative modeling of replacement decisions. This essay aims to explicitly integrate into a quantitative model three special roles of an incumbent product in replacement decisions, specifically, a) shaping choice set formation, b) serving as the reference point to evaluate new products and c) imposing mental costs on consumers. The proposed model addresses both the questions of a) is now the time to replace? and b) if so, which new product should be the replacement?

To capture the special roles of the incumbent product in replacement decisions, I propose a new choice model that characterizes replacement decisions as a two-stage process (see Figure 2-1): 1) a higher-level decision on whether to replace, i.e., forming a choice set that only includes the incumbent product (corresponding to no replacement) or a choice set that only includes the new products (corresponding to replacement); 2) a lower-level decision on what to choose conditional on replacement. At the higher level, the likelihood of replacement depends on three interacting components (i.e., the attributes of the incumbent product, its age, and consumer characteristics) as well as the evaluation of the overall attractiveness of the new products. At the lower level, the choice of a new product conditional on replacement depends on either the reference-dependent or reference-independent evaluation of the new products.

-------------Figure 2-1--------------

The contribution of this research is three-fold. First, I propose a new perspective for conceptualizing replacement decisions. The conventional perspective is that individuals compare and trade-off all the available options, i.e., the incumbent as well as the new products, and then select the best alternative among them, which may or may not lead to replacement. In this perspective, the incumbent product is treated no differently from the new alternatives. I propose, however, a fundamentally different perspective of replacement decisions, in which a corresponding choice set is formed based on the higher-level decision on whether to replace (see Figure 2-1), and the attributes of the incumbent product are not traded-off against the attributes of the new products but simply influence the higher-level decision on whether to replace. The results from this research provide strong support for this perspective versus the conventional one on replacement decisions.

Second, I provide empirical evidence that consumers, when replacing point-and-shoot digital cameras (the product category used in the choice experiment), use their incumbent product as the reference point to evaluate new products and exhibit significant loss-aversion effects (i.e., they are more sensitive to losses than to gains). Although prospect theory predicts such findings, one could also argue that consumers might be reluctant to use their incumbent product as the referent because the incumbent product might be obsolete at the time of replacement. However, I find that about 98% of the consumers in the sample use their incumbent product as the reference point. I also find that the likelihood of using the incumbent product as the reference point is a function of the age of the incumbent product and consumers' maximization tendency (Schwartz et al. 2002).

Third, this research helps "triangulate" previous behavioral findings on mental cost formation in replacement decisions (Okada 2001, 2006). Okada (2001) has shown through lab experiments that 1) consumers create a mental account upon purchasing a product and then start a mental depreciation process based on the positive experience obtained from using the product and 2) replacement forces consumers to write-off the remaining book value of this mental account, a process that causes pain to (or impose mental costs on) consumers because it makes them feel they have not obtained enough worth from the product. I find that the parameter estimates of the proposed model are consistent with this proposed theory on mental cost formation in replacement decisions (detailed discussion is provided subsequently).

In the remaining parts of the essay, I first review the existing research on replacement decisions and discuss the extant theories in support for the special roles of the incumbent product in replacement decisions. I then develop a new choice model that explicitly incorporates these roles into the model specification. I next describe the data collected for this research, test the new model on the data, and discuss the main results. After that, a policy experiment is conducted to show the different policy predictions made by the new versus the conventional model. Finally, I conclude the findings, point out the limitations of the current paper, and discuss the opportunities for future research.

2.2 THE ROLES OF THE INCUMBENT PRODUCT IN REPLACEMENT DECISIONS

Given the importance of replacement in the sales of durable goods, both the economics and marketing literatures have documented various quantitative research on consumer replacement decisions. In the economics literature, for example, Rust (1987) proposes an optimal stopping model to characterize bus engine replacement; Fernandez (2000) adopts a similar model to investigate household replacement decisions about electric heaters and air conditioners; Raymond, Beard and Gropper (1993) employ a hazard model to examine home heating system replacement decisions. An earlier paper in the marketing literature by Bayus and Gupta (1992) investigates consumer replacement decisions for a set of home appliances using a Binary Logit model. More recent work Prince (2008) studies replacement demand for PCs employing a model that allows for forward-looking behavior (see Rust 1987) but assumes that consumers have perfect foresight about future product price and quality. Gordon (2009) further develops the replacement model along this line by explicitly accounting for uncertainty about future price and quality. Although such progression of the replacement models helps better understand replacement decisions, especially about the timing of replacement, previous endeavors in this area have largely ignored the special roles that could be potentially played by incumbent products in replacement decisions. Understanding these roles is both theoretically and practically important, as these roles influence not only whether to replace but also what to choose as a replacement (given that one has decided to replace). In the following section I provide detailed discussions about these roles.

The First Role: Directing Choice Set Formation

Choice set formation theory (Manski 1977) and empirical work (Andrews and Srinivasan 1995; Swait and Ben-Akiva 1987a,b; among others) suggest that consumers may first form a choice set and then choose an alternative from the choice set. This two-stage decision process is consistent with a benefit-cost tradeoff view (see review by Hauser forthcoming). Following this rationale, I propose that when faced with a choice context with multiple options as replacement, a consumer will first form a choice set based on whether to replace or not, and then choose a new product conditional on replacement. More specifically, if s/he decides not to replace, a choice set is formed that only includes the incumbent product; whereas if s/he decides to replace, a choice set is formed that only includes new products. In this sense the incumbent product serves as the pivotal option that directs choice set formation, which reflects the higher-order decision on whether to replace or not (see Figure 2-1).

Recognizing this special role of the incumbent product provides a new perspective on replacement decisions. Within this new perspective, replacement decisions are viewed as a two-stage instead of a single-stage process as viewed by the conventional perspective on replacement decisions. Specifically, the conventional perspective assumes that consumers compare and trade-off between all products, both incumbent and new, at the same level of the decision hierarchy and then make a choice which may or may not lead to replacement. The proposed new perspective differs from the conventional one not only in the number of decision hierarchies but also in the role of the incumbent product in evaluation. Formally, the new perspective is proposed from two related aspects:

Proposition 1a: In replacement decisions, consumers first decide whether to replace (i.e., the higher-level process of forming a choice set that only includes the incumbent product or one that only includes new products) and then decide what new product to choose conditional on replacement (i.e., the lower-level process).

Proposition 1b: The features of the incumbent product are not compared with those of the new products in the lower-level evaluative process but directly influence the higher-level decision on whether to replace.

The Second Role: Serving as the Reference Point to Evaluate New Products

Prospect theory (Kahneman and Tversky 1979) predicts that products are evaluated with respect to a certain reference point and that individuals are more sensitive to losses than to gains. It is possible that consumers who have decided to replace use their incumbent product as the reference point to evaluate new options. The reason is two-fold. First, the incumbent product is usually operational at the time of replacement and thus serves as relevant comparison point. Second, the incumbent product represents a “status quo” state and it is natural for individuals to compare a new state with the “status quo”. Actually, the incumbent product has been pervasively used as the reference point in previous studies on prospect theory and status quo effect (e.g., Bateman et al. 1997; Kahneman, Knetsch and Thaler 1990; Kahneman and Tversky 1979; Knetsch 1989; Samuelson and Zeckhauser 1988; Thaler 1980; Tversky and Kahneman 1991).

But it is also possible that the incumbent product is not used as the reference point because it might be obsolete or simply too different from current products in the market to be considered relevant for comparison.[1] Under such circumstances, one possibility is that consumers engage in reference-*independent* evaluation. Given the relevance of the incumbent product that might determine reference-*dependent* vs. reference-*independent* evaluation, I predict that

P1: Conditional on replacement, the likelihood of engaging in reference-*dependent* evaluation based on the incumbent product decreases as the age of the incumbent product increases.

Another factor that might influence the likelihood of reference-*dependent* evaluation is an individual’s maximizer tendency, which is defined as the

[1] Admittedly other possibilities for reference points exist, e.g., ideal composites defined by aspirational levels of attributes, or a specific camera to which the decision maker has been exposed. In this research we set these possibilities aside as a future research opportunity.

inclination to choose the "best" instead of the "good enough" option (see Schwartz et al. 2002). As maximizers always want the best, they may focus on the best available product in the current market and hence disregard their incumbent product as the reference point. Therefore, I predict that

P2: Conditional on replacement, the likelihood of engaging in reference-*dependent* evaluation based on incumbent products decreases as an individual's maximizer tendency increases.

It is important to recognize these two evaluation modes (reference-*dependence* and -*independence*) in replacement decisions and the factors that may determine the selection of the evaluation modes, as the choice of replacement options is directly influenced by the evaluation mode taken by consumers. In addition, evaluation modes also indirectly influence the higher-level decision on whether to replace through influencing the overall attractiveness of the new options.

The Third Role: Imposing Mental Costs on Consumers

The third special role of the incumbent product is suggested by the mental cost theory proposed by Okada (2001). This theory has three components. First, consumers create a mental account upon the purchase of a product, and the initial book value of that account is equal to the price paid for that product. Second, during the period of using the product, this mental account is depreciated and the degree of depreciation depends on the amount of positive experience obtained from the product usage. Specifically, the more positive experience a consumer has obtained from the product usage, the greater the mental depreciation made. The rationale is that positive experience makes the consumer feel that the money paid for the product was worthwhile. Third, if s/he decides to replace, the consumer has to write-off the remaining value of the mental account. This action causes pain to the consumer, who incurs a mental cost because s/he may feel that the remaining book value of the account is wasted. Taken together, this theory on mental cost formation during replacement decisions suggests that the incumbent product functions as a barrier to replacement and that the extent to which the incumbent product hinders replacement depends on the amount of the remaining book value of the mental account. More specifically, the greater the remaining book value, the greater the mental cost and the lower the likelihood of replacement.

Since this remaining book value of the account increases as the initial price of the incumbent product increases, decreases as the incumbent product becomes old (due to the longer period of depreciation), and decreases as consumers are more involved in the product (given that more positive experience is likely to be obtained by more involved consumers), I predict that:

P3: The likelihood of replacement decreases as the price paid for the incumbent product increases;

P4: The likelihood of replacement increases as the age of the incumbent product increases;

P5: The likelihood of replacement increases as consumers are more involved with the product.

Note that P3 is also known as the sunk cost effect that has been widely documented by behavioral research (e.g., Arkes and Blumer 1985; Dick and Lord 1998; Garland and Newport 1991). In addition to the above predictions on the main effects of the three factors (price, age of the incumbent product, consumer involvement), there may also be interaction effects among the three factors. First, it is possible that the sunk cost effect (P3) decreases as the incumbent product becomes old. The reason is that a longer period of elapsed time may help consumers better realize that the cost paid for the incumbent product has already been "sunk" and that they should ignore it in decision-making. Hence, consumers with old incumbent products may be less sensitive to the remaining book value of the mental account. Therefore, I predict a two-way interaction between the price and the age of the incumbent product. Formally,

P6: The sunk cost effect decreases as the age of the incumbent product increases.

It is also possible that there is a three-way interaction among the price, the age of the incumbent product, and consumer involvement. Specifically, for consumers with old incumbent products, the sunk cost effect may further decrease as their product involvement increases; but for consumers with new incumbent products, their product involvement may not have too much influence on the sunk cost effect. The reason can be traced back to the origin of what prevents individuals from ignoring sunk cost: the reluctance to admit that the prior investment has been wasted (Arkes and Blumer 1985). For consumers with older incumbent products, high-involvement individuals are likely to suffer from such reluctance much less than low-involvement individuals, because this reluctance is likely to be decreased greatly by the joint effect of the longer usage period and the high involvement level. However, for those consumers with relatively new incumbent products, that reluctance is likely to be preponderant for both high- and low-involvement consumers: after all, the incumbent product is still new and a strong sense of wasting the prior investment is likely to exist regardless of the product involvement level. Therefore, I predict a three-way interaction between the price of the incumbent product, its age, and consumer involvement as follows:

P7: For consumers whose incumbent products are older, the sunk cost effect decreases as product involvement increases; but for consumers whose incumbent products are relatively new, the sunk cost effect does not decrease as product involvement increases.

P3-P7 jointly reflect the underlying process of mental cost formation in replacement decisions (Okada 2001), in which the incumbent product plays a pivotal role. Incorporating this role of the incumbent product into replacement decisions is important as the mental cost formation process directly influences the higher-level decision on whether to replace.

To summarize, the incumbent product can play three special roles in replacement decisions: 1) providing a basis upon which replacement or non-replacement choice set is constructed, 2) serving as the reference point against which new options are compared, and 3) functioning as a barrier to replacement through imposing mental costs on consumers. To capture these special roles of the incumbent product in replacement decisions, I develop a new choice model which

I specify in the subsequent section.

2.3 MODEL SPECIFICATION

I develop a new choice model, which I refer to as the Multistage Replacement Choice Model (MRCM), to explicitly integrate the above-mentioned roles of the incumbent product in replacement decisions. The MRCM is developed on the basis of the GenL choice set generation GEV model (see Swait 2001). The probabilistic structure of the MRCM is shown in Figure 2-2, which corresponds to the two-stage replacement decisions as depicted in Figure 2-1.

I first provide an overview of how the MRCM captures the three roles of the incumbent product in replacement decisions. Specifically, to capture the first role (i.e., directing choice set formation), the MRCM characterizes a hierarchical structure that includes a higher-level choice set formation stage and a lower level evaluation stage as shown in Figure 2-2. To capture the second role (i.e., serving as the reference point), the MRCM incorporates two evaluative modes at the lower level: 1) reference-dependent evaluation based on the incumbent product or 2) reference-independent evaluation (see Figure 2-2). To capture the third role (i.e., imposing mental costs on consumers), the MRCM incorporates three interacting factors, the price of the current product, its age and consumer involvement into the replacement probability function that corresponds to the higher level of the model structure (again, see Figure 2-2).

-------------Figure 2-2--------------

Based on Figure 2-2, the unconditional probability of choosing the incumbent product in a choice scenario t by individual n is

$$P_{nt}(INC) = Q_{nt}(NoREP) \tag{1}$$

where $Q_{nt}(NoREP)$ is the probability of making the higher-level decision of no replacement (or forming a choice set that only includes the incumbent product) by individual n at choice scenario t. For succinctness, the subscripts of n, t are suppressed hereafter. On the other hand, the unconditional probability of choosing a new product k is

$$\begin{aligned} P(k) = [&P(k \mid REP, RD) \cdot Q(RD \mid REP) + \\ &P(k \mid REP, RID) \cdot Q(RID \mid REP)]Q(REP) \end{aligned} \tag{2}$$

where

$$Q(REP) = 1 - Q(NoREP), \tag{3}$$

$$Q(RD \mid REP) = 1 - Q(RID \mid REP), \tag{4}$$

$Q(REP)$ is the probability of making the higher-level decision of replacement (or forming a choice set that only includes the new products),

$Q(RD \mid REP)$ ($Q(RID \mid REP)$) is the probability of engaging in reference-dependent (reference-independent) evaluation conditional on replacement, and

$P(k \mid REP, RD)$ ($P(k \mid REP, RID$) is the conditional probability of choosing new product k given replacement and reference-dependent (reference-independent) evaluation.

In the next section I describe the specifications of each of the above probabilities in a top-down sequence based on the hierarchical structure as represented in Figure 2-2.

Probability of Replacement

I first specify the likelihood of the higher-level decision on whether to replace or not. Based on the GenL model (Swait 2001), I specify the probability of no replacement as

$$Q(NoREP) = \frac{\exp(\mu(I_{INC} + \lambda E))}{\exp(\mu(I_{INC} + \lambda E)) + \exp(\mu I_{NEW})}, \tag{5}$$

where

$$I_{INC} = \mu_1 \beta_{INC} x_{INC}. \tag{6}$$

Specifically, I_{INC} is the attractiveness of the incumbent, x_{INC} is the vector of attributes of the incumbent product, and β_{INC} is the corresponding parameter vector. The root scale is termed μ, μ_1 (μ_2) is the scale of the choice set corresponding to no replacement (replacement) (see Figure 2-2). For identification purpose, μ and μ_1 have to be normalized to 1 (see Swait 2001 for further discussion). E is the vector of all the other variables that influence whether to replace, such as the age of the incumbent product, individual characteristics, etc.. λ is the corresponding parameter vector. Finally, I_{NEW} is the evaluation of the overall attractiveness of all the new options after accounting for both reference-dependent and reference-independent evaluative modes (the full specification of I_{NEW} is presented subsequently).

The existence of I_{NEW} in Eq. 5 suggests that the higher-level decision on whether to replace is context-dependent, that is, the more attractive the assortment of the new products is, the more likely a consumer decides to replace. This is consistent with the notion that the higher-level decision on whether to replace is influenced by the incremental benefit of replacement vs. non-replacement, given that the benefit of replacement is measured by the overall attractiveness of the assortment of replacement options. On the other hand, λE in Eq. 5 suggests that the higher-level decision on whether to replace also has a context-independent component, that is, individuals' prior propensity to replace. This prior propensity is a function of individual characteristics such as consumer involvement with the product category. The inclusion of both the context-*dependent* and context-*independent* components in Eq. 5 suggests that the decision on whether to replace is jointly influenced by both a top-down and a bottom-up process (Weber and Johnson 2009), that is, a consumer enters into a choice situation with a certain preset propensity to replace (top-down), which is in turn adjusted by the overall attractiveness of the presented assortment of replacement options (bottom-up).

I now describe the specific variables included in x_{INC} and E given the particular data set for this research. Specifically, x_{INC} includes the following attributes of the currently-owned point-and-shoot digital cameras: brand, price, resolution, zoom, LCD size, wide-angle functionality and camera size. I predict a positive sign for the price coefficient based on P3.

E includes the key variables used to test P4-P7, plus covariates. The key variables are the age of incumbent cameras, consumers' product involvement, price-by-age interaction, price-by-age-by-involvement interaction. I predict a negative sign for the age coefficient based on P4, a negative sign for the involvement coefficient based on P5, a negative sign for the price-by-age interaction based on P6, and a negative sign for the price-by-age-by-involvement interaction based on P7. Note that Eq.5 is about the probability of no replacement, $Q(NoREP)$, so the predicted signs are associated with the probability of staying with the incumbent product instead of the probability of replacement as described in P3-P7.

The covariates included in E are a constant, consumers' maximizer tendency, expertise, income, presented set size (= -1, if two new products are presented; =1, if four new products are presented), brand-by-age interaction, price-by-maximizer interaction, price-by-expertise interaction, age-by-involvement interaction, age-by-maximizer interaction, age-by-expertise interaction, maximizer-by-price-by-age and expertise-by-price-by-age interaction. I predict a negative sign for the income coefficient, because it is likely that more affluent consumers are less likely to stick with the incumbent product than those with lower income. I also predict a positive sign for presented set size, as consumers might be more likely to stick with the incumbent product in a complex (i.e., four new products are presented) than in an easy choice situation (i.e., two new products are presented), given the choice overload effect (Iyengar and Lepper 2000).

In addition, I have the following predictions about the covariates associated with the maximizer tendency. First, I predict a negative sign for the maximizer tendency, because maximizers (i.e., who strive to obtain the best available option, Schwartz et al. 2002) might be less likely to stick with the incumbent product than non-maximizers (i.e., satisficers, Schwartz et al. 2002). Second, a positive sign for the maximizer-by-price interaction, because the effect of maximizer tendency on replacement likelihood is likely to be mitigated by the sunk cost effect. Third, I predict a negative sign for the maximizer-by-price-by-age interaction, because the maximizer-by-price interaction is likely to be weaker for old incumbent cameras than for new incumbent cameras given that the sunk cost effect for old incumbent cameras might have become too small to offset the effect of maximizer tendency on replacement likelihood. Fourth, a negative sign for the maximizer-by-age interaction is predicted, as maximizers might be even more likely to replace an old than a new incumbent product. With respect to the other covariates, I have no specific predictions. All the predicted signs associated with the probability of no-replacement (i.e., staying with the incumbent product) are summarized in the lower panel of Table 2-3 (which is presented subsequently).

Thus far I have specified the factors that might influence replacement likelihood, which is associated with the higher-level choice set formation stage as depicted in the model structure (see Figure 2-2). In the following section, I move down to a lower level of the decision hierarchy (see Figure 2-2) and examine the two evaluative modes: reference-*dependent* (based on the incumbent product) and reference-*independent* evaluation.

The Probability of Engaging in Reference-Dependent Evaluation

I specify the probability of engaging in reference-*independent* evaluation as,

$$Q(RID \mid REP) = \frac{\exp(\mu_2 \gamma Z)}{1 + \exp(\mu_2 \gamma Z)}, \tag{7}$$

where μ_2 is the scale of the choice set corresponding to replacement, i.e., the choice set that only includes the new products (see Figure 2-2; for detailed discussion about choice set scales see Swait 2001), Z is the vector of variables that potentially influence the probability of taking reference-*independent* evaluation, and γ is the corresponding parameter vector.

In the particular data for this research, Z includes the key variables used to test P1 and P2, plus covariates. The key variables are the age of the incumbent product and a consumer's maximizer tendency. I predict a positive sign for the age of the incumbent product based on P1, and a positive sign for consumers' maximizer tendency based on P2. Note that Eq. 7 is about the probability of reference-*independent* evaluation given replacement, $Q(RID \mid REP)$, so the predicted signs are associated with this probability, instead of the probability of taking reference-*dependent* evaluation as stated in P1 and P2.

The covariates included in Z are a constant, consumers' involvement, expertise and income. I predict a positive sign for income, since it is likely that more affluent consumers, as compared to poorer consumers, are more probable to focus on the best available option in the current market and thus more likely to engage in reference-*independent* evaluation. For other covariates, I have no specific predictions. All the predicted signs associated with the probability of reference-independent evaluation are summarized in the upper panel of Table 2-3 (which is presented subsequently).

After specifying the probability of making reference-independent vs. reference-dependent evaluations, I move further down the decision hierarchy (see

Figure 2-2) to specify how consumers choose a new product based on either reference-independent or reference-dependent evaluation in the next section.

The Conditional Choice Probability Given Replacement Based on Reference-Dependent or Reference-Independent Evaluation

In this section, I focus on specifying the conditional probability of choosing a new product given replacement based on either reference-dependent or reference-independent evaluation. First, based on the reference-independent evaluative mode, the conditional probability of choosing new product *k* given replacement is simply

$$P(k \mid RID, REP) = \frac{\exp(\mu_2 \beta_{NEW}^{RID} x_k)}{\sum_{k'=1}^{K} \exp(\mu_2 \beta_{NEW}^{RID} x_{k'})}, \quad (8)$$

where K is the total number of new products presented, x_k is the vector of attributes of the *k*'th new product (i.e., price, resolution, zoom, LCD size, wide-angle functionality and camera size for the specific data set for this research), β_{NEW}^{RID} is the corresponding coefficients based on reference-independent evaluation. Note that β_{NEW}^{RID} is different from β_{INC} in Eq.5. This is because I must allow for differential evaluation of the new products compared to the evaluation of the incumbent product. Such specification allows us to test whether the attributes of the incumbent product directly influence the higher-level decision on whether to replace, or they are traded off with the attributes of the new products at the lower-level evaluation stage (see Figure 2-2).

Second, based on reference-dependent evaluation, the conditional probability of choosing new product k given replacement is

$$P(k \mid RD, REP) = \frac{\exp(\mu_2(\beta_{NEW}^{GAIN} x_k^{GAIN} + \beta_{NEW}^{LOSS} x_k^{LOSS} + \beta_1 WA_k + \beta_2 WA_k WA_{INC} + \beta_3 CS_k + \beta_4 CS_k CS_{INC}))}{\sum_{k'=1}^{K} \exp(\mu_2(\beta_{NEW}^{GAIN} x_{k'}^{GAIN} + \beta_{NEW}^{LOSS} x_{k'}^{LOSS} + \beta_1 WA_{k'} + \beta_2 WA_{k'} WA_{INC} + \beta_3 CS_{k'} + \beta_4 CS_{k'} CS_{INC}))} \tag{9}$$

where x_k^{GAIN} (x_k^{LOSS}) is the vector of gain- (loss-) variables for continuous attributes (i.e., price, resolution, zoom and LCD size) of the k^{th} new product, and β_{NEW}^{GAIN} (β_{NEW}^{LOSS}) is the corresponding parameter vector. WA_k (WA_{INC}) is wide-angle functionality of the new (incumbent) camera, and CS_k (CS_{INC}) is camera size of the new (incumbent) camera. For these two discrete variables (wide-angle functionality, camera size), I use the interaction terms ($WA_k WA_{INC}, CS_k CS_{INC}$) to capture reference-dependent evaluation. For the continuous attributes that are positively correlated with camera attractiveness (i.e., resolution, zoom and LCD size),

$$x_k^{GAIN} = \max((x_k - x_{INC}), 0), \tag{10}$$

$$x_k^{LOSS} = \min((x_k - x_{INC}), 0) . \tag{11}$$

But for the attribute of price that is negatively correlated with camera attractiveness,

$$x_k^{GAIN} = \max((x_{INC} - x_k), 0) , \tag{12}$$

$$x_k^{LOSS} = \min((x_{INC} - x_k), 0) . \tag{13}$$

The above coding scheme for gain- and loss- variables is based on Hardie, Johnson and Fader (1993). The reason why the gain- and loss- variables are defined differently for resolution, zoom and LCD size than for price is that higher resolution, zoom, or LCD as compared to the reference point is considered as gain but lower price as compared to the reference point is considered as gain. Separate gain- and loss-parameters (i.e., β_{NEW}^{GAIN}, β_{NEW}^{LOSS}) are used because in reference-dependent evaluation consumers are likely to respond more dramatically to losses than to gains (the loss aversion effect, see Kahneman and Tversky 1979). I test subsequently the existence of the loss aversion effect for each of the continuous attributes (price, resolution, zoom, and LCD size).

Now I specify the overall attractiveness of the new products (I_{NEW}) to complete the specification of the probability of no replacement $Q(NoREP)$ (see Eq. 5). As previously discussed, the reason why I_{NEW} can influence $Q(NoREP)$ is that the higher-level decision on whether to replace not only depends on the exogenous variables (e.g., the price, age of the incumbent product, individual characteristics), but also on the endogenous lower-level evaluative processes. I_{NEW} is the summary measure of the evaluative processes as it represents the overall attractiveness of the assortment of new products. Given the existence of two evaluative modes in the proposed model, I_{NEW} should account for both the reference-dependent and reference-independent evaluative processes. Specifically,

$$I_{NEW} = \frac{1}{\mu_2} \ln(\exp(\mu_2 I_{NEW}^{RD}) + \exp(\mu_2 (I_{NEW}^{RID} + \gamma Z))) \tag{14}$$

where

$$I_{NEW}^{RD} = \frac{1}{\mu_2}\ln(\sum_{k=1}^{K}\exp(\mu_2(\beta_{NEW}^{GAIN}x_k^{GAIN} + \beta_{NEW}^{LOSS}x_k^{LOSS} + \beta_1 WA_k + \beta_2 WA_k WA_{INC} + \beta_3 CS_k + \beta_4 CS_k CS_{INC}))) \tag{15}$$

$$I_{NEW}^{RID} = \frac{1}{\mu_2}\ln(\sum_{k=1}^{K}\exp(\mu_2(\beta_{NEW}^{RID}x_k))). \tag{16}$$

Specifically, I_{NEW}^{RD} (I_{NEW}^{RID}) is the expected maximum attractiveness of all the presented new products based on reference-dependent (reference-independent) evaluation. All the other variables are the same as previously defined.

Based on the probability of no replacement $Q(NoREP)$, the probability of reference-independent evaluation given replacement $Q(RID \mid REP)$, and the conditional probability of choosing a new alternative given replacement based on each evaluation mode (i.e., $P(k \mid RD, REP)$, $P(k \mid RID, REP)$), I can compute the unconditional probability of choosing the incumbent product $P(INC)$ (see Eq.1) and the unconditional probability of choosing a new product *k* $P(k)$ (see Eq.2). Using $P_{nt}(i_{nt}*)$ as the notation for the unconditional probability of choosing the chosen alternative $i_{nt}*$ by individual *n* at choice scenario *t*, I specify the likelihood function as

$$L = \prod_n \prod_t P_{nt}(i_{nt}*). \tag{17}$$

Note that the chosen alternative $i_{nt}*$ can be either the incumbent product or any of the new products. Also note that the subscripts *n* and *t* have been suppressed in the above specifications (from Eq.2 - Eq.16) for succinctness.

2.4 DATA COLLECTION

The data used for this research were collected through a conjoint choice experiment on point-and-shoot (P&S) digital cameras. Specifically, the data were collected via an online survey, using a commercial North American online panel. Respondents were required to own a P&S camera to be eligible to participate. The data include 500 participants, each of whom was given 15 hypothetical choice scenarios in which either 2 or 4 new cameras were presented (i.e., within-subject manipulation of the two conditions: 2-new-cameras or 4-new-cameras); they could choose either to replace their incumbent camera with one of these new cameras or to stay with their incumbent product (Figure 2-3 displays a screen shot of a choice scenario under the 4-new-camera condition). To ensure that participants understood the replacement context, they were told that they must sell or give away their incumbent camera if they choose one of the new cameras. After completion of the choice tasks, participants were asked about the features of their incumbent camera, its age, their product involvement level and maximizer propensity (based on the maximizer scale developed by Schwartz et al. 2002), in addition to other data not used in model estimation. The survey took approximately 15-20 minutes to complete. The summary statistics regarding the product attributes of the incumbent and new cameras, other related variables and choice are presented in Table 2-1.

-------------Table 2-1, Figure 2-3--------------

I employed a presence/absence experimental design by including 2 or 4 out of 15 cameras, all of which were available in the market at the time when the survey was conducted. As shown in Figure 2-3, the new cameras were presented via a picture as well as the actual specifications on resolution, zoom, LCD size, wide-angle capability and camera size, plus price. All these attributes were held constant for a camera whenever it was shown, except for price which was manipulated ±15% around the actual retail value of the specific camera model. The design intent of 1) using these currently available cameras, 2) posting pictures along with actual attribute specifications and 3) anchoring the price manipulation on actual retail value was to make the new cameras in the choice scenarios appear as real as the incumbent product, with which participants may have had a significant amount of experience.

2.5 ESTIMATION RESULTS

I estimate the MRCM based on the data I have collected. The model estimates are presented in Table 2-2. Corresponding to the modeling structure (see Figure 2-2), Table 2-2 has three parts: probability of no replacement (Part 1), probability of reference-independent evaluation (Part 2), and conditional choice probability given replacement based on either reference-dependent or reference-independent evaluation (Part 3.1 and 3.2). I discuss the results revolving around the previously mentioned three special roles of the incumbent product in replacement decisions: directing choice set formation, serving as the reference point to evaluate new products, and functioning as a barrier to replacement by imposing mental costs on consumers.

-------------Table 2-2--------------

The First Role: Directing choice set formation

First, I test whether the incumbent product helps direct choice set formation in replacement decisions (Proposition 1a). To test for this role of the incumbent product, I estimate a competing model that does not incorporate choice set formation. More specifically, in this competing model all products are evaluated within the universal choice set, which includes both the incumbent and the new products. Similar to the MRCM, the competing model also includes both the reference-dependent or reference-independent evaluation. I find that this competing model fits the data significantly worse that the MRCM: the BIC for the competing model is 16058, which is 156 points greater than the BIC of the proposed model (15902). This result provides support for Proposition 1a, which suggests a new perspective on replacement decisions, that is, on in which consumers first form a choice set based on the higher-level decision on whether to replace and then choose a new product conditional on replacement. Stated differently, the result shows that it is unlikely that consumers evaluate all the alternatives (both the incumbent and the new products) in a universal choice set as suggested by the conventional perspective on replacement decisions.

Given the support for Proposition 1a as discussed above, I now test Proposition 1b (the attributes of the incumbent product are not traded off with those of the new products but directly influence the higher-level decision on whether to replace) to provide further support for the new perspective on replacement decisions. Specifically, I test the null hypothesis that the attribute coefficients for the incumbent product (i.e., price, resolution, zoom, LCD size, wide-angle functionality, camera size in Part 1 of Table 2-2) are equal to the corresponding coefficients for new products (see Part 3.2 of Table 2-2). I find that the null hypothesis is rejected (p-value≈0.000) using a Likelihood Ratio test. Stated differently, it is found that the attributes of the incumbent and new products are evaluated in different ways. This suggests that the attributes of the incumbent product are not likely to be traded off with those of the new products in the universal choice set. Instead, in light of two-stage decision-making as previously found (i.e., support for Proposition 1a), the attributes of the incumbent product are likely to directly influence the higher-level decision on whether to replace.

Based on the support for Proposition 1a and Proposition 1b (the two related aspects of the new perspective on replacement decisions), I can easily interpret the distinctively different coefficients for the same product attribute of the incumbent and the new products. For example, I find that a consumer does not prefer an incumbent camera with high zoom factor (the corresponding coefficient in Part 1 of Table 2-2 is -1.617) although s/he prefers a new camera with high zoom (the corresponding coefficient in Part 3.2 of Table 2-2 is 4.325). In light of the new perspective on replacement decisions, the above results can be simply explained by the possibility that a consumer who has enjoyed the benefits of high zoom in the incumbent product is more likely to upgrade to a new product with even higher zoom factor.

The Second Role: Serving as the Reference Point to Evaluate New Products

In this section I focus on investigating the role of the incumbent product as the reference point in evaluation. The result shows that the average probability of engaging in reference-dependent evaluation based on the incumbent product is 98% in the sample used for this research. To formally test the significance of reference-dependent evaluation, I estimate a competing model that does not incorporate the reference-dependent evaluation mode but simply a reference-independent evaluation mode. In this competing model, I retain the high-level choice set formation. I find that the goodness-of-fit for the competing model dramatically decreases as compared to the full MRCM: the BIC of the competing model (16239) is 337 points higher than the BIC of the MRCM (15902). This result suggests that consumers are much more likely to use than to not use their incumbent product as the reference point in replacement decisions for the product category of point-and-shoot digital cameras. It is possible that for technology products like digital cameras the replacement is more likely to be driven by obsolescence than by deterioration. As a result, consumers may replace rather frequently (2.5 years on average between replacements in the sample) and use their incumbent product as the reference point, as their incumbent products are likely to be still considered as functional and relevant at the time of replacement.

After testing the existence of reference-dependent evaluation, I further test the existence of loss aversion by using a likelihood ratio test. Specifically, to test whether consumers respond more dramatically to the losses in price than to the corresponding gains, for example, I set the null hypothesis that the coefficient of PriceGain is equal to that of PriceLoss. If the null hypothesis is rejected, I conclude that there is significant loss aversion effect for price. This test is repeated for each of the other attributes, i.e. resolution, zoom and LCD size. I find that the loss aversion effect is significant for price (p-value≈0.000) and zoom (p-value≈0.000) but not significant for resolution (p-value≈0.122) and LDC size (p-value≈0.553).

Regarding the key variables that influence the selection of evaluation model, I find support for P1 and P2. Specifically, the results show that consumers who own older cameras (P1) and who have stronger maximizer tendencies (P2) are more likely to make reference-independent evaluations. Considering the covariates that might influence evaluation mode selection, I find that higher income consumers are more likely to make reference-independent evaluation. The summary of both predicted and estimated signs of the corresponding coefficients can be found in the upper panel of Table 2-3, and the exact parameter estimates can be found in Part 2 of Table 2-2.

-------------Table 2-2; Table 2-3--------------

The Third Role: Functioning as a Barrier to Replacement by Imposing Mental Costs on Consumers

In this section I investigate how the incumbent product functions as a barrier to replacement by imposing mental costs on consumers. To achieve this objective, I examine whether the results are consistent with the predictions (P3-P7) based on mental cost formation theory proposed by Okada (2001). The parameter estimates of the proposed MRCM provide support for all these predictions (P3-P7). Specifically, I find that consumers are less likely to make a replacement if they have paid a high price for their incumbent camera (stated differently, the existence of a sunk cost effect is supported) (P3); they are more likely to replace an old incumbent camera than a new incumbent camera (P4); high-involvement consumers are more likely to replace than low-involvement consumers (P6); the sunk cost effect decreases as incumbent products become old (P6); for older incumbent cameras, the sunk cost effect is smaller for high-involvement than for low-involvement consumers; but it is not the case for new incumbent cameras (P7). These results suggest that the incumbent product functions as a barrier to replacement by imposing mental costs to consumers according to the underlying mechanism as proposed by Okada (2001). The summary of the predicted and estimated sign for the corresponding coefficients can be found in the lower panel of Table 2-3, and the specific parameter estimates can be found in Part 1 of Table 2-2.

To summarize, I have found support for three special roles of the incumbent product in replacement decisions: directing choice set formation, serving as reference points and imposing mental most on consumers.

Other Findings: The Influence of Other Factors on Replacement Likelihood

In the above analyses, I have provided empirical evidence for the special roles of the incumbent product in replacement decisions. After controlling for these special roles of the incumbent product in replacement decisions, one can better understand how other factors, including both contextual and individual characteristics, influence the higher-level decision on whether to replace or not. For example, I find as predicted that consumers who are presented with larger choice set are more likely to stay with the incumbent product, and that consumers with higher income and/or stronger maximizer tendency are less likely to stick with the incumbent product. Note that the full list of the comparison between the predicted and estimated effects of the covariates can be found in the lower panel of Table 2-3.

A close examination of this list reveals that the results support all the predictions about the covariates except the one about maximizer-by-age interaction. Specifically I predicted that maximizers would be more likely to replace an older incumbent product; instead I find the opposite. This could be explained by the possibility that longer ownership/usage period may prove to maximizers that the incumbent product they considered as the best at the time of purchase is indeed a good one. As a result, they may be more complacent about the "right" choice previously made and thus more reluctant to make a replacement as compared to satisficers.

2.6 POLICY ANALYSIS

In the above section, I have discussed results based on the MRCM that have incorporated three special roles of the incumbent product in replacement decisions. In this section, I compare the Willingness To Pay (WTP) measures for attribute changes based on the MRCM to the counterparts based on the conventional model, which omits these roles of the incumbent product (i.e., the Multinomial Logit Model). Specifically, I first compute WTPs based on the MRCM for a) increasing resolution from 12.1 to 14 megapixel, b) increasing zoom from 3 to 5 times, c) increasing LCD size from 3.0 to 3.5 inches, d) adding wide-angle functionality, and e) decreasing camera size from compact case needed to pocket size respectively. Then I compute the corresponding WTP measures based on the simple Multinomial Logit (MNL) Model.

I find that, as shown in Figure 2-4, the MNL model greatly overestimates the WTP measures as compared to the MRCM. This result suggests that accounting for the above-mentioned special roles of the incumbent product in replacement decisions lead to significantly different implications for new product designs. Given that the previous tests have supported the above-mentioned roles of the incumbent product and that the MNL model has much poorer goodness-of-fit (BIC=16326) as compared to the MRCM (BIC=15902), the WTP measures based on the MRCM are likely to be more reliable than those based on the MNL model. The detailed procedures of calculating the corresponding WTP measures can be found in the Appendix 2-1.

-------------Figure 2-4--------------

2.7 CONCLUSION AND FUTURE RESEARCH

In this research, I propose three special roles of the incumbent product in replacement decisions: directing choice set formation, serving as the reference point to evaluate new products and imposing mental costs on consumers. I develop a new choice model (the Multistage Replacement Choice Model – MRCM) to explicitly represent these three roles. I estimate the MRCM based on data collected from a choice experiment about point-and-shoot digital cameras. Through the corresponding tests, I find support for the proposed three special roles of the incumbent product in replacement decisions. I also discuss a consequence of ignoring these roles in choice modeling, that is, generating unreliable WTP measures that may misdirect marketing strategies about new product designs.

The contribution of this paper is three-fold. First, I propose a new perspective of two-stage replacement decisions in which the attributes of the incumbent product contribute to making the higher-level decision on whether to replace or not, instead of being traded off with the attributes of the new products in the lower-level evaluative process. Second, I provide an empirical evidence for the use of the incumbent product as the reference point in replacement decisions about point-and-shoot digital cameras. Third, this research helps triangulate the previous behavioral findings from lab experiments about mental cost formation in replacement decisions (Okada 2001).

Although the MRCM has accounted for taste heterogeneity in terms of incorporating two evaluative modes, reference-dependent and reference-independent evaluation, I have not allowed for taste heterogeneity conditional on either of the evaluative modes. Given that the focus of this paper is to investigate the roles of the incumbent product in replacement decisions, I leave the examination of taste heterogeneity conditional on reference-dependent or reference-independent evaluation for future research.

Another limitation of this research is that I have not allowed for the possibility that consumers use other candidates than their incumbent product as the reference point for reference-dependent evaluation. It is possible that some consumers use their ideal product as the reference point. Under such circumstances, the majority of the new product attributes are likely to be perceived as losses with respect to this highly attractive reference point (i.e., the ideal product). Given the possibly low incidences of gains in such cases, the reference-dependent evaluation based on the ideal product can be partially mimicked by reference-*independent* evaluation. As the selection of reference points is by itself a complicated and interesting question, I leave the incorporation of multiple possible reference points for future research.

The roles of the incumbent product in forward-looking replacement decisions deserve investigation in future research. The existing forward-looking replacement models based on time-series data (e.g., Gordon 2009; Rust 1987) have provided insights into the dynamics of replacement decisions, especially about the timing of replacement. Incorporating the roles of the incumbent product into these models may lead to better understanding on the interplay of these roles with the dynamics of replacement decisions, for example, how the expectations of the future product price and quality influence the likelihood of engaging in reference-dependent vs. reference-independent evaluation.

2.8 TABLES

Table 2-1 Summary Statistics of Product Attributes and Other Variables

Variable	Mean	Std Dev	Min	Max
Product Attributes for Incumbent Cameras				
Price ($)	243.20	92.67	50	375
Resolution (mega pixel)	7.82	3.03	2	15
Zoom (times)	5.19	3.26	2	15
Lcd Size (inch)	2.49	0.53	1.5	4
Wide Angle (-1 for no; 1 for yes)	-0.10	0.85	-1	1
Camera Size (-1 for pocket size; 1 for compact case needed)	0.02	1.00	-1	1
Product Attributes for New Cameras				
Price ($)	251.69	88.97	119.95	399.95
Resolution (mega pixel)	11.29	1.28	8	12.1
Zoom (times)	5.09	2.26	3	12
Lcd Size (inch)	2.83	0.28	2.5	3.5
Wide Angle (-1 for no; 1 for yes)	-0.33	0.98	-1	1
Camera Size (-1 for pocket size; 1 for compact case needed)	-0.07	1.03	-1	1
Other Variables				
Age of the Incumbent Camera (month)	30.99	24.55	1.00	208.00
Involvement (0-5, from low to high involvement)	3.30	1.33	0.00	5.00
Maximizer Tendency (1-7, from extreme satisficer to extreme maximizer)	3.88	0.93	1.00	7.00
Expertise (0-1,from low to high expertise)	0.51	0.22	0.00	1.00
Annual Household Income (thousand $)	101.38	52.51	10.00	200.00
Presented Set Size (-1 for 2 new cameras presented; 1 for 4 new cameras presented)	0.26	0.97	-1.00	1.00
Choices				
Incumbent Camaras	54%			
New Cameras	46%			

Table 2-2 Parameter Estimates of the Multistage Replacement Choice Model (MRCM)

Part 1: Probability of No-Replacement (i.e., Staying with the Incumbent Product)

Incumbent Product Attributes, Age, and Individual Characteristics		Interactions	
Sony	-0.862(0.164)***	Sony*Age	8.065(2.601)***
Canon	-0.716(0.158)***	Canon*Age	7.476(2.575)***
Panasonic	-0.931(0.188)***	Panasonic*Age	13.375(2.775)***
Fujifilm	-0.724(0.195)***	Fujifilm*Age	7.911(2.881)***
Kodak	-1.285(0.182)***	Kodak	8.429(2.648)***
Casio	-0.865(0.233)***	Casio*Age	12.492(3.173)***
Nikon	-1.206(0.187)***	Nikon*Age	8.71(2.789)***
Olympus	-0.586(0.179)***	Olympus*Age	7.271(2.714)***
Samsung	0.455(0.359)	Samsung*Age	11.357(4.313)***
Price	1.551(0.223)***	Price*Age	-4.295(1.362)***
Resolution	-0.9(0.317)***	Price*Involvement	0.85(0.584)
Zoom	-1.617(0.336)***	Price*Maximizer	2.792(0.976)***
LcdSize	-0.398(0.314)	Price*Expertise	1.455(0.672)**
WideAngle	0.161(0.035)***	Age*Involvement	-1.414(1.257)
CameraSize	0.014(0.029)	Age*Maxmizer	9.848(2.342)***
(IncumbentProduct)Age	-10.534(2.517)***	Age*Expertise	-1.575(1.493)
Involvement	-0.508(0.126)***	Price*Age*Involvement	-15.449(5.22)***
Maximizer(Tendency)	-1.327(0.209)***	Price*Age*Maxmizer	-43.7(12.374)***
Expertise	0.856(0.147)***	Price*Age*Expertise	43.631(6.89)***
Income	0.117(0.101)	Constant	1.89(0.173)***
PresentedSetSize	0.066(0.035)*		

Part 2: Probability of Reference-Independent Evaluation Conditional on Replacement

(IncumbentProduct)Age	14.081(4.659)***
Maximizer(Tendency)	36.716(13.445)***
Involvement	1.568(4.234)
Expertise	-6.525(5.877)
Income	9.204(5.274)*
Constant	-15.218(5.415)***

Part 3.1: Conditional Choice Probability Given Replacement based on Reference-Dependent Evaluation		**Part 3.2: Conditional Choice Probability Given Replacement based on Reference-Independent Evaluation**	
Sony	0.368(0.073)***	Sony	1.102(0.454)**
Canon	0.444(0.064)***	Canon	0.66(0.426)

(continued)

Table 2-2 (cont.)

Part 3.1: Conditional Choice Probability Given Replacement based on Reference-Dependent Evaluation		**Part 3.2: Conditional Choice Probability Given Replacement based on Reference-Independent Evaluation**	
PriceGain	0.215(0.131)	Price	-1.5(0.843)*
PriceLoss	2.047(0.216)***	Resolution	-0.443(1.698)
ResolutionGain	1.036(0.221)***	Zoom	4.325(1.479)***
ResolutionLoss	1.474(0.323)***	LcdSize	2.172(1.601)
ZoomGain	1.12(0.184)***	WideAngle	0.215(0.187)
ZoomLoss	3.673(0.36)***	CameraSize	-0.513(0.261)**
LcdSizeGain	0.818(0.216)***		
LcdSizeLoss	0.689(0.244)***		
WideAngle	0.354(0.041)***		
CameraSize	-0.079(0.037)**		
WideAngle*Incumbent ProductWideAngle	0.013(0.019)		
CameraSize*Incumbent ProductCameraSize	0.09(0.017)***		

Choice Set Scales (logarithm)

Choice Set Containing the Incumbent Product	---Fixed at 0---
Choice Set Containing the New Products	0.324(0.091)***

Goodness of Fit

#of Parameters	70	AIC	15417
LogLikelihood	-7638	BIC	15902

Calculation Based on Model Estimates

Average Probability of Replacement	0.46
Average Probability of Reference-dependent Evaluation Conditional on Replacement	0.98

1. Standard errors in (), ***refers to p-value<0.01,**refers to 0.01<p-value<=0.05, *refers to 0.05<p-value<=0.1
2. All nominal scales are effect coded.
3. Brands are dummy coded.
4. All interval and ratio scales are mean-centered: transformed value= (original value-mean)/(max-min). As a result, the transformed values all approximately fall within the range of (-0.5,0.5).

Table 2-3 The Summary of the Predicted and Estimated Signs of the Parameter Estimates of the MRCM

Probability of Reference-Independent Evaluation

Predictions about Key Variables			Covariates with Predictions			Covariates without Predictions	
Variables	Predicted Sign	Estimated Sign	Variables	Predicted Sign	Estimated Sign	Variables	Estimated Sign
(IncumbentCamera)Age	+ (based on P1)	+	Income	+	+	Involvement	NS*
Maximizer(Tendency)	+ (based on P2)	+				Expertise	NS
						Constant	-

Probability of No-Replacement (i.e., Staying with the Incumbent Product)

Predictions about Key Variables			Covariates with Predictions			Covariates without Predictions	
Variables	Predicted Sign	Estimated Sign	Variables	Predicted Sign	Estimated Sign	Variables	Estimated Sign
(IncumbentCamera)Price	+(based on P3)	+	Income	-	-	Involvement*Price	NS
(IncumbentCamera)Age	- (based on P4)	-	PresentedSetSize	+	+	Involvement*Age	NS
Involvement	- (based on P5)	-	Maximizer(Tendency)	-	-	Expertise	+
Price*Age	- (based on P6)	-	Maximizer*Price	+	+	Expertise*Age	NS
Price*Age*Involvement	- (based on P7)	-	Maximizer*Age	-	+	Expertise*Age*Price	+
			Maximizer*Price*Age	-	-	Sony*Age	+
						Canon*Age	+
						Panasonic*Age	+
						Fujifilm*Age	+
						Kodak*Age	+
						Casio*Age	+

(continued)

Table 2-3 (cont.)

		Nikon*Age	+
		Olympus*Age	+
		Samsung*Age	+
		Constant	+

*NS refers to non-significant statistically based on α=0.1.

2.9 FIGURES

Figure 2-1 Two-Stage Replacement Decision Making

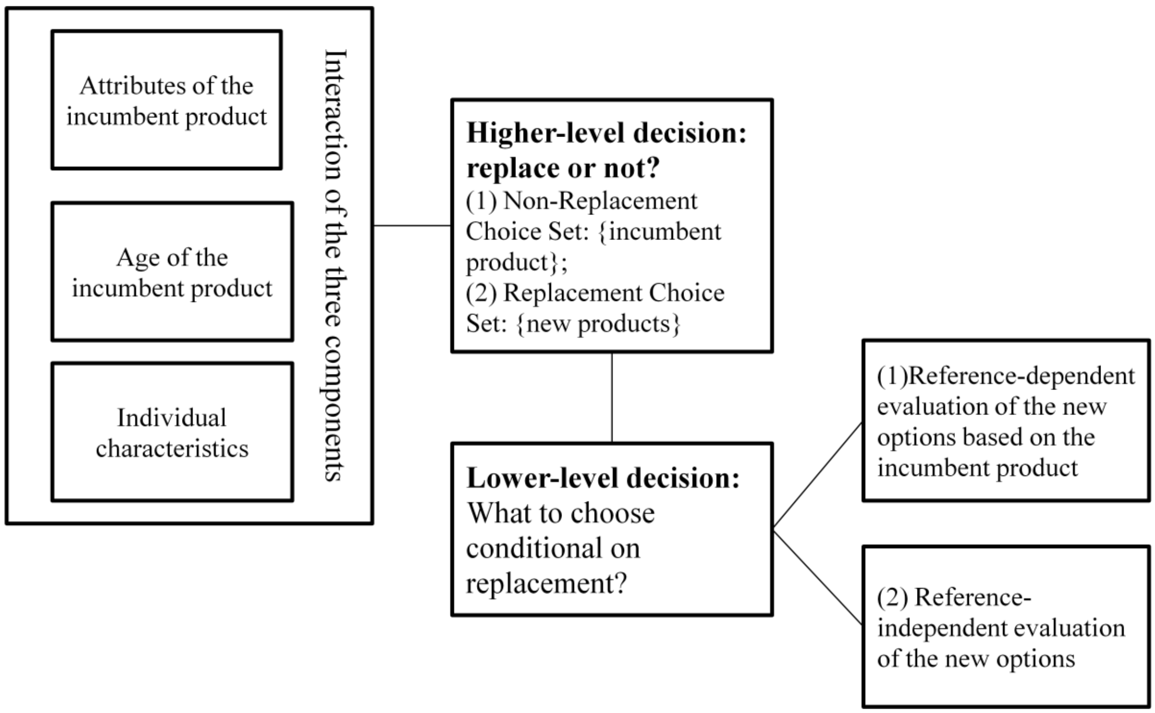


Figure 2-2 Structure of the Multistage Replacement Choice Model (MRCM)

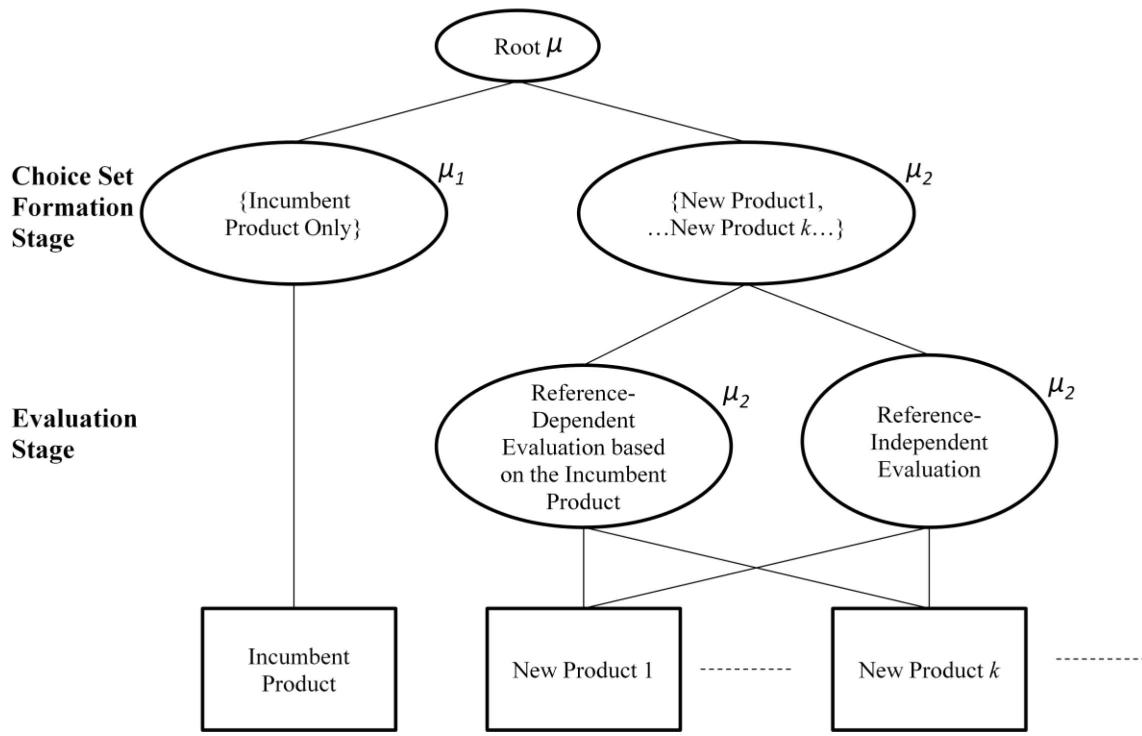


Figure 2-3 A Screenshot of a Choice Scenario Under the Condition of Four New Cameras

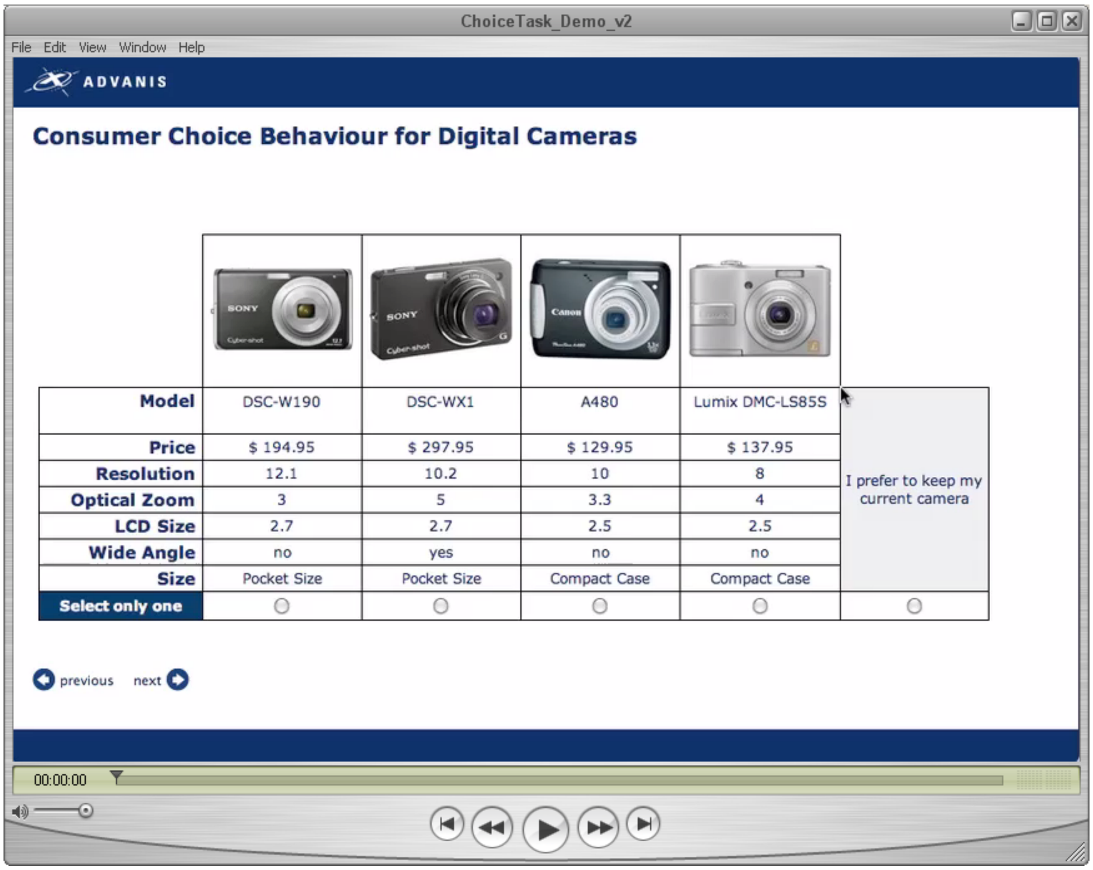
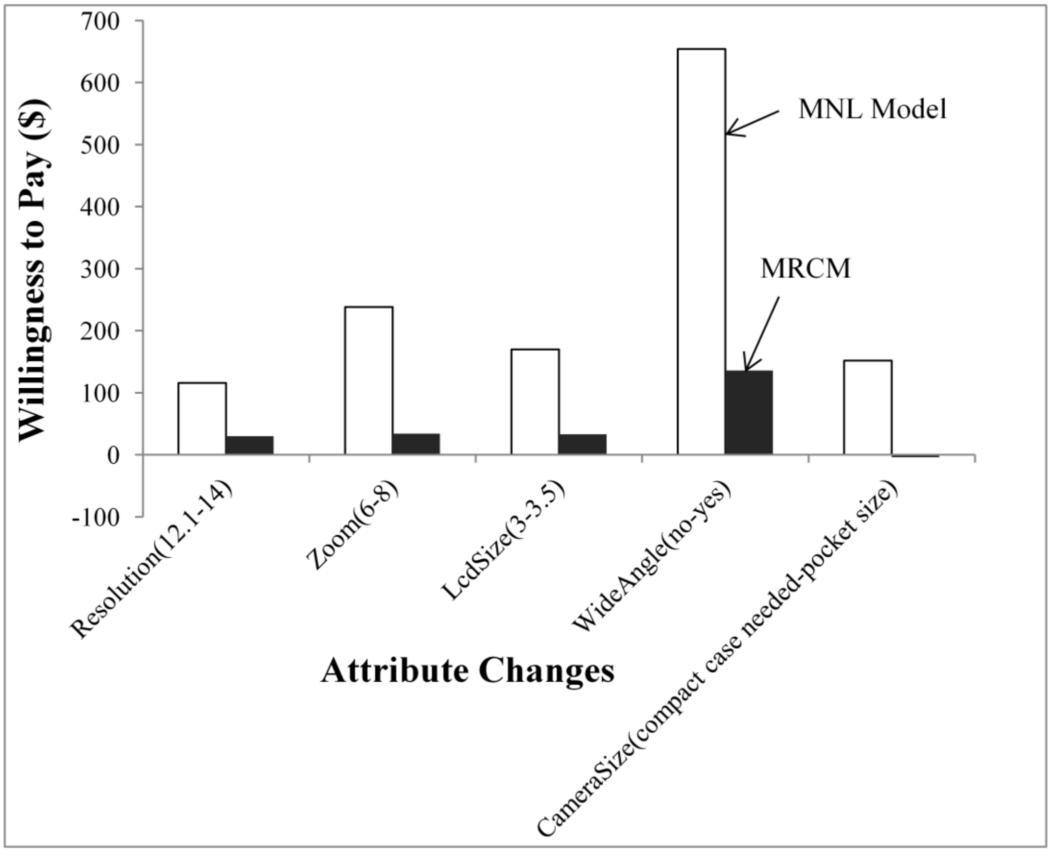


Figure 2-4 Comparison of WTP Measures Based on the MRCM vs. MNL Model



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3. MODELING SIMULTANEOUS MULTIPLE GOAL PURSUIT IN CONSUMER PRODUCT CHOICE

This essay incorporates another type of antecedent volition, goal pursuit, into the modeling of consumer choice-making processes. Specifically, I propose an integrated framework of simultaneous multiple goal pursuit in product choice, which explicitly accounts for the central role of goals in consumer evaluative processes and choice behavior. The new framework includes three key components: (a) prior goal weighting (i.e. consumers, prior to product evaluation, decide on the desired emphasis among multiple simultaneous goals based on their general attitude towards them), (b) goal-specific attribute evaluation (i.e., consumers evaluate product attributes in terms of how they help achieve each activated goal) and (c) goal weight adaptation (i.e., upon realizing the actual goal attainability of a choice scenario a result of (b), consumers adjust their prior goal weights by assigning greater weights to more attainable goals).

This framework suggests that consumers arrive at a choice scenario with multiple active goals with respect to which product attributes are evaluated (i.e., goal activation is an antecedent to evaluation). This perspective is fundamentally different from the conventional framework, since my proposal positions goals, rather than some abstract measure generically termed "utility", as the core metrics of evaluation; it further allows these goals to interact (influence and be influenced by) the choice context. I test the proposed framework with a new goal-based choice model that explicitly characterizes the three key components of the framework as mentioned above.

It deserves noting that in the previous chapter (i.e., Chapter 2) I assumed that utility is the core measure of evaluation so that the investigation is focused on one type of antecedent volition (i.e., replacement strategies), which is expressed through choice set formation. In this chapter, I assume no choice set formation so as to focus on the role of goals in consumer choice. The interplay of these two forms of antecedent volition (i.e., strategies and goals) is left for future research.

3.1 INTRODUCTION

Although psychology and consumer behavior research has provided ample evidence that the goals play a critical role in decision-making (e.g., Dhar and Simonson 1999; Ferguson and Bargh 2004; Fishbach and Dhar 2005; Köpetz et al. 2012; Laran and Janiszewski 2009; Markman and Brendl 2000; Markman, Brendl and Kim 2007; van Osselaer and Janiszewski 2012), to date the development of choice models has remained silent about the role of goals. Integrating goals into choice modeling is important both theoretically and practically, since ignoring goals may lead to a) inaccurate policy predictions due to the omission of the underlying mechanism of goal-based choice (see the Lucas Critique, Lucas 1976) and b) loss of insights into the consumer “black box” that may help develop innovative marketing programs (McFadden 1986). The objective of the present research is to develop a behavioral framework of goal-based choice and, from that, a corresponding operational choice model that explicitly incorporates goals (i.e., consumption benefits) into its formulation and specification.

Based on relevant behavioral theories, I first propose an integrated framework of simultaneous multiple goal pursuit within a single product choice (see Figure 3-1), as consumers often attempt to achieve multiple goals simultaneously (Atkinson and Birch 1970; Köpetz et al. 2011; Neisser 1963). Under this framework, a consumer driven by multiple simultaneous goals 1) enters a choice situation with a prior set of goal weights based on his/her pre-determined judgment on goal attractiveness (Kernan and Lord 1990; Schmidt and DeShon 2007), 2) evaluates product attributes in terms of how well they help attain each of the multiple goals (e.g., Markman and Brendl 2000; van Osselaer and Janiszewski 2012), 3) adapts his/her prior goal weights to the goal attainability of the choice context (i.e., the product assortment) by assigning more (less) weights to more (less) attainable goals (Kernan and Lord 1990; Schmidt and Dolis 2009), and finally 4) selects a product that best achieves his/her multiple goals based on the adapted goal weights. Second, I propose a new goal-based choice model to represent this proposed framework. Third, I employ the proposed model to empirically test the behavioral framework with choice data on point-and-shoot digital cameras.

--- Figure 3-1 about here ---

The contribution of this research is three-fold. First, it proposes a new goal-based conceptualization of choice, in which goals are the core measure for evaluation instead of *utility* as in the conventional microeconomic framework (Lancaster 1966). One might argue that this goal-based conceptualization of choice can be incorporated by the existing utility-based view, as *utility* can be considered an overarching measure that encompasses all the lower-level goals. That is, *utility* can be expressed as $u = W_1 A_1 + W_2 A_2$ (assuming a simple two-goal case, W_1, W_2 are the goal weights, and A_1, A_2 are the corresponding goal attainments). This utility-based view is at best a *reduced-form* conceptualization of goal-based choice, because it ignores the interplay between the underlying behavioral determinants of goal-based choice since goal weighting (W_1, W_2) depends on goal attainments (A_1, A_2) as consumers tend to assign greater weights to more attainable goals (Kernan and Lord 1990; Schmidt and Dolis 2009). If a goal-driven process is represented via a *reduced-form* utility-based view, this leads to inaccurate policy predictions (this is the essence of the Lucas Critique, Lucas 1976). This research provides empirical support for this observation and thus lends support to the new goal-based conceptualization of choice.

Second, I advance choice modeling by developing a new choice model form on the basis of the new goal-based conceptualization of choice. Not only does this new model predict choice better, but also it separates two distinct constructs that are confounded by the existing utility-based choice models: (a) goal importance and (b) attribute importance to goal attainment. To illustrate this confound in the utility-based models, I use the above-mentioned two-goal example wherein *utility* is expressed as $u = W_1 A_1 + W_2 A_2$. Suppose there are two attributes x_1 , x_2, and ψ_{lk} reflects the importance of the l^{th} product attribute to attaining goal *k*. Then, goal attainments can be expressed as $A_1 = \psi_{11} x_1 + \psi_{21} x_2$ and $A_2 = \psi_{12} x_1 + \psi_{22} x_2$. Substitute A_1, A_2 in the above utility function for these two expressions of goal attainments, then $u = W_1(\psi_{11} x_1 + \psi_{21} x) + W_2(\psi_{12} x_1 + \psi_{22} x) = (W_1 \psi_{11} + W_2 \psi_{12}) x_1 + (W_1 \psi_{21} + W_2 \psi_{22}) x_2$. Since the coefficient for each product attribute ($W_1 \psi_{11} + W_2 \psi_{12}$ or $W_1 \psi_{21} + W_2 \psi_{22}$) can only be estimated as a single parameter usually termed the *preference* or *taste* parameter, the utility-based models cannot separate the two distinct constructs: (a) goal importance (W) and (b) attribute importance to goal attainment (ψ). But, as will be demonstrated, the proposed goal-based model can separate the two constructs, and as a result, provide additional insights into consumers' goal-driven choice behavior that may help marketers develop innovative targeting, positioning and new product designing strategies.

Third, I add to the existing goal-based consumer choice literature (see Köpetz et al. 2012; van Osselaer and Janiszewski 2012) by showing goal weight adjustment within a single choice. Previous research has focused on goal weight revision over multiple choice periods/occasions due to goal progress or satiation (e.g., Dhar and Simonson 1999; Fishbach and Dhar 2005; Laran and Janiszewski 2009; Wang and Mukhopadhyay 2012). I provide empirical evidence for within-choice goal weight adjustment, to wit, that consumers adapt their pre-determined goal weights to the actual goal attainability of a specific product assortment presented in a choice context. Understanding such within-choice goal weight adjustment is of theoretical importance because it recognizes the interplay, within a single choice, of a top-down goal-directed behavior with a bottom-up context-dependent property (Weber and Johnson 2009).

I organize the remainder of this chapter as follows: I present the behavioral framework, develop a new choice model to characterize the framework and then test the model with consumer choice data about point-and-shoot (P&S) digital cameras. Next, I conduct policy analyses based on the proposed model. This is followed by a discussion of the findings and the limitations of the research, and the identification of future research opportunities.

3.2 RELATED RESEARCH IN MULTIPLE-GOAL DECISION-MAKING

Definition of Goals

Consistent with previous research I define a goal as a motivational, cognitive concept that determines behavior (van Osselaer and Janiszewski 2012). In the present research I focus on a specific subcategory of goals, consumption-benefit goals. Consumption benefits function as goals because consumers' expectation of consumption benefits serves as the underlying motivation for product evaluations and choices (van Osselaer and Janiszewski 2012). I further classify consumption-benefit goals into higher-level abstract goals and lower-level functional goals, based on the nature of consumption benefits (i.e., abstract vs. functional benefits) and the existence of goal hierarchies (Kruglanski et al. 2002). I put greater emphasis on functional goals in the present research given that functional goals are more likely to be predictive of choice as they are closer to the observed choices in terms of construal level as compared with abstract goals (see *Construal Level Theory*, Trope and Liberman 2010).

Existing Research on Quantitative Modeling of Multiple-Goal Decision-Making

Quantitative modeling of multiple-goal decision-making can be traced back to early economic literature (e.g., Baumol 1957, 1962; Cooper 1949; Ferguson 1965; Reder 1947) that aimed to solve multiple-goal *business* problems, such as maximizing the present value of the firm's net worth subject to retaining corporate control (Cooper 1949; Reder 1947), or maximizing sales provided a satisfactory level of profit (Baumol 1957). Multiple-goal decision-making is later introduced into management science by Charnes and Cooper (1961), which generated a large body of research known as *goal programming* to solve various multiple-objective *management* problems, such as maintaining market leadership while avoiding bankruptcy (see review by Chang 2007). Multi-attribute utility models are also employed to address multiple-objective management problems, with the specific managerial goals treated as the attributes in the model (Keeney and Raiffa 1976). Although the extant research on multiple-goal modeling provides insights into solving multiple-objective business/management problems, to my best knowledge no existing research has explicitly incorporated goals into the modeling of *consumers'* product choice that is driven by multiple simultaneous goals. In the present research, I aim to propose a new choice model specification that characterizes consumers' multiple-goal-based choice-making processes. The proposed model is developed on the basis of an integrated behavioral framework of simultaneous multiple goal pursuit in consumer product choice as subsequently described.

A Framework of Simultaneous Multiple Goal Pursuit in Consumer Product Choice

I propose a framework of multiple-goal-based choice that consists of three key components: (a) prior goal weighting, (b) goal-specific attribute evaluation and (c) goal weight adaptation (see Figure 3-1). Prior goal weighting refers to the process wherein consumers determine the importance of goals prior to product evaluation. Specifically, prior goal weights are a function of goal attractiveness (i.e., how attractive each goal appears to a consumer independently of the specific decision context; see Kernan and Lord 1990, Schmidt and DeShon 2007), which might be strongly determined by individual characteristics (e.g., consumption experience, social demographics).

Goal-specific attribute evaluation involves the process of evaluating product attributes in terms of how well they contribute to each goal and making judgments about the degree to which each goal is attained. This proposed process is in line with ample evidence in behavioral research that suggests that goals serve as the core measure for evaluation in consumer choice (e.g., Dhar and Simonson 1999; Fishbach and Dhar 2005; Fishbach, Dhar, and Zhang 2006; Köpetz et al. 2012; Laran and Janiszewski 2009; Markman and Brendl 2000; van Osselaer and Janiszewski 2012; Zhang, Fishbach and Dhar 2007).

Goal weight adaptation refers to the process of adjusting prior goal weights given the realization of actual goal attainability of the presented product assortment. It is likely that individuals adjust their prior goal weights in such a way that more (less) weight is allocated to more (less) attainable goals (Kernan and Lord 1990; Schmidt and Dolis 2009). It is also likely that this goal weight adaptation is an iterative process, in which consumers keep adapting their prior goal weights upon realizing the actual attainability of each goal until no goal weights need to be adapted and a choice can be made. Since the specifics of this dynamic process are unknown to researchers (e.g., which goals are adapted first, which goals are adapted and which are not, the extent of goal adaptation), I conceptualize goal weight adaption as an anchor-and-adjustment process in which the final adapted goal weights depart from the prior goal weights (i.e., the anchor) to some degree. To characterize this adjustment process, I conceptualize each consumer as a *mixture* of a full-adaptation and no-adaptation archetypes, with the mixture probability representing the tendency to adapt. Specifically, consumers with a greater tendency to adjust may adapt more goals and/or adapt individual goal importance to a greater extent. It is possible that the tendency to adapt is related to consumers' willingness to be flexible in a product choice, which might be a function of consumer characteristics such as product usage experience and expertise.

The above-mentioned framework of multiple-goal-based choice cannot be represented by the existing utility-based models as commonly understood (e.g., Hanemann 1984), since these models ignore the underlying behavioral mechanism of goal-based choice as included in the framework by directly mapping product attributes onto a summary measure called *utility*. As a consequence, utility-based models fail to separate goal importance from attribute importance to goal attainment (i.e., the two distinct constructs that are important to marketers) and may produce inaccurate policy predictions (Lucas 1976). Given these limitations, I propose a new choice model that explicitly represents the proposed framework of simultaneous multiple goal pursuit in product choice. The details of the model specification are presented as follows.

3.3 DEVELOPMENT OF A NEW MULTIPLE-GOAL-BASED CHOICE MODEL

In this section, I develop a new Multiple-Goal-Based Choice Model (hereafter referred to as the MGBCM) to characterize the proposed framework of simultaneous multiple goal pursuit in consumer product choice (see Figure 3-1). The MGBCM treats goals as the latent constructs and explicitly incorporates them into the model specification. In the following, I first specify each of the three components in the proposed framework and then integrate them to specify the likelihood function.

Prior Goal Weighting

As previously mentioned, a consumer, prior to evaluating products, weights the goals on the basis of how inherently attractive each goal is to him/her. This prior attitude toward goal attractiveness is formed before any evaluative processes are initiated. Thus, it is not influenced by the choice context, but is predetermined by individual characteristics, such as product usage experience and socio-demographics. I express the prior goal weights as follows:

$$W_{nk} = \frac{\exp(\gamma_k Z_n)}{\sum_{k'=1}^{K} \exp(\gamma_{k'} Z_n)}, \tag{1}$$

where W_{nk} is the prior goal weight that consumer *n* assigns to goal *k*, Z_n is the vector of individual characteristics, γ_k is the goal-specific parameter vector for Z_n, K is the total number of goals a consumer strives to achieve. For identification purpose, γ_1 (i.e., the parameters for the individual characteristics with respect to the first goal) is fixed at zero. (Any goal can be used as the referent.)

Goal-Specific Attribute Evaluation

Again as previously discussed, a consumer evaluates products based on how well the attributes help attain each goal. Stated differently, the attainment of goals serves as the core measure for evaluation. I use A_{ntki} to denote this core measure for evaluation, which represents the extent to which alternative *i* assists consumer *n* at choice scenario *t* to attain goal *k*. Specifically,

$$A_{ntki} = \overline{A_{ntki}} + \varepsilon_{ntki} = \psi_k x_{nti} + \varepsilon_{ntki}, \tag{2}$$

where $\overline{A_{ntki}}$ is the systematic component of A_{ntki}, x_{nti} is the attribute vector of alternative *i* in choice scenario *t* evaluated by individual *n*, ψ_k is the corresponding *importance* vector representing the usefulness of product attributes in attaining goal *k*, and ε_{ntki} is the unitscale Gumbel distributed error term (independent across products). Note that ψ_k is goal-specific, suggesting that the same product attribute can contribute differentially to different goals. For example, camera resolution may contribute to the goal of "taking good pictures" more than to the goal of "having a camera that is easy to use." As I shall see next, A_{ntki} also serves as the basis of goal weight adaptation.

Goal Weight Adaptation

Previously we suggested that a consumer may adapt his/her prior goal weights W_{nk} based on the actual goal attainability of a choice scenario so that more (less) cognitive resources are allocated to more (less) attainable goals (Kernan and Lord 1990; Schmidt and Dolis 2009). For consumer *n*, the attainability of goal *k* from choice scenario *t* is the maximum attainability of goal *k* from the product assortment presented in the choice scenario, i.e., $\max(A_{ntk1}, A_{ntk2}, ..., A_{ntkJ})$, *J* being the total number of alternatives in the choice scenario. However, $\max(A_{ntk1}, A_{ntk2}, ..., A_{ntkJ})$ is unknown to researchers due to the existence of the stochastic component in the evaluation of goal attainability (see ε_{ntki} in Eq. 2). As a result, researchers can only resort to the *expected* maximum attainability of goal *k* over *J* alternatives in the choice scenario. The expected maximum of a group of independent and identically distributed Gumbel random variables can be expressed as follows (Ben-Akiva and Lerman 1985, p104-105):

$$I_{ntk} = E(\max(A_{ntk1}, A_{ntk2}, ..., A_{ntkJ})) = \frac{1}{\mu_k} \ln \sum_{j=1}^{J} \exp(\mu_k \overline{A_{ntkj}}), \quad (3)$$

where I_{ntk} (also referred to as inclusive value) is the expected maximum value of

$A_{ntk1}, A_{ntk2},..., A_{ntkJ}$, and μ_k is the goal-specific scale of the Gumbel distributed error ε_{ntki} .

Thus, from researchers' perspective, I can define the *fully* adapted goal weight W_{ntk}' as a function of both individual characteristics that determine the prior goal weight Z_n and the expected maximum goal attainability of a choice scenario I_{ntk} , specifically,

$$W_{ntk}' = \frac{\exp(I_{ntk} + \gamma_k Z_n)}{\sum_{k'=1}^{K} \exp(I_{ntk'} + \gamma_{k'} Z_n)} \tag{4}$$

where I_{ntk} is as defined Eq. 3, and $\gamma_k Z_n$ is as defined in Eq. 1. Note that Eq. 4 shows how the interplay between the underlying behavioral determinants (goal attainments via I_{ntk}, and prior goal weights via $\gamma_k Z_n$) is incorporated into the model specification.

In order to understand the impact of goal scales μ_k on adapted goal weights, I substitute Eq. 3 for I_{ntk} in Eq. 4,

$$W_{ntk}' = \frac{\exp(\frac{1}{\mu_k} \ln \sum_{j=1}^{J} \exp(\mu_k \overline{A_{ntkj}}) + \gamma_k Z_n)}{\sum_{k'=1}^{K} \exp(\frac{1}{\mu_{k'}} \ln \sum_{j=1}^{J} \exp(\mu_{k'} \overline{A_{ntk'j}}) + \gamma_{k'} Z_n)} \; . \tag{5}$$

It is observed that the greater the μ_k , the weaker the influence of the systematic component of goal attainability ($\overline{A_{ntkj}}$) on goal weighting (note that the impact of μ_k in the component of $\frac{1}{\mu_k}$ dominates its impact in the component of $\ln \sum_{j=1}^{J} \exp(\mu_k \overline{A_{ntkj}})$ on W_{ntk}'). This suggests that μ_k is able to capture the sensitivity of goals to the influence from the choice context. Specifically, the greater μ_k , the weaker the sensitivity of goal k to the choice context. I return to this topic subsequently.

Incorporating Goal Weight Adaptation Tendency into the Model Specification

As mentioned above W_{ntk}' is the *fully* adapted goal weight, since Eq. 4 assumes that consumers adapt all goals, each to a full extent (note that the coefficient for I_{ntk} in Eq. 4 is fixed at unity). As previously discussed, we assume that each consumer is conceptualized as a *mixture* of a full-adaptation and no-adaptation archetypes; in this specification, W_{ntk}' represents the final goal weights used by the full-adaptation archetype, whereas the prior goal weights W_{nk} (in Eq. 1) represents the final goal weights used by the no-adaptation archetype (see the overall mixture structure as described in Figure 3-2). It is now necessary to account for consumers' tendency to adapt by representing each decision maker as a mixture of the two archetypes. Specifically, I define consumer *n*'s unconditional probability of a choice sequence T_n as

$$P_n(T_n) = P_n(T_n \mid Adapt) * Q_n^{Adapt} + P_n(T_n \mid NoAdapt) * Q_n^{NoAdapt}. \qquad (6)$$

where Q_n^{Adapt} ($Q_n^{NoAdapt}$) is the probability of the decision maker adopting the pure full-adaptation (no-adaptation) archetype. Note that in this framework, Q_n^{Adapt} represents the tendency to adapt. $P_n(T_n \mid Adapt)$ ($P_n(T_n \mid NoAdapt)$) is consumer *n*'s conditional probability of choosing a choice sequence T_n given the full-adaptation archetype (no-adaptation archetype).

--- Figure 3-2 about here ---

To specify the factors that may influence Q_n^{Adapt}, the tendency to adapt, I predict that consumers with greater objective (subjective) knowledge/expertise have stronger (weaker) tendency to adapt, since previous research has shown that objective knowledge facilitates the use of newly inquired information while subjective knowledge increases the reliance on previously stored information (Rudell 1979). Thus, I model the tendency to adapt Q_n^{Adapt} as a function of consumers' objective expertise (i.e., in the data about camera choice used for this research, whether or not the consumer owns a SLR, the frequency of taking trips specifically for photography) and subjective expertise (i.e., self-reported expertise about cameras). Specifically, I adopt the logistic functional form for this model component:

$$Q_n^{Adapt} = \frac{1}{1+\exp(\lambda E_n)}, \tag{7}$$

where E_n is the vector of variables including both objective and subjective expertise, and λ is the corresponding parameter vector. Symmetrically, the tendency towards no-adaptation is

$$Q_n^{NoAdapt} = 1 - Q_n^{Adapt}. \tag{8}$$

As previously mentioned, the full-adaptation archetype relies on the adapted goal weights (W_{ntk}') that are context-dependent (i.e., a consumer adapts his/her goal weights to each choice context); whereas the no-adaption archetype uses the prior goal weight W_{nk} that is context-independent throughout all choice scenarios. As context-dependence is the only difference between the two archetypes, to empirically identify the two archetypes I must require that each individual complete multiple choice tasks, wherein the two different patterns of goal weight variation can be displayed by the two archetypes.

Specifying the Likelihood Function

The likelihood function for the MGBCM is the product of unconditional choice sequences over individuals n=1,…,N, which is

$$L = \prod_n P_n(T_n) = \prod_n (P_n(T_n \mid Adapt) * Q_n^{Adapt} + P_n(T_n \mid NoAdapt) * Q_n^{NoAdapt}), \qquad (9)$$

where is $P_n(T_n)$ specified as in Eq. 6. Now I specify the conditional choice probabilities on each archetype, $P_n(T_n \mid Adapt)$ and $P_n(T_n \mid NoAdapt)$, respectively.

First, conditional on the full-adaptation archetype, the probability of choosing a choice sequence T_n by consumer n is,

$$P_n(T_n \mid Adapt) = \prod_t P_{nt}(i_{nt}^* \mid Adapt) \;, \qquad (10)$$

where i_{nt}^* is the chosen alternative at choice scenario t in the choice sequence T_n by individual n, $P_{nt}(i_{nt}^* \mid Adapt)$ is the conditional probability of choosing alternative i_{nt}^* given the full-adaptation archetype. As $P_{nt}(i_{nt}^* \mid Adapt)$ has accounted for all goals, a full expression of $P_{nt}(i_{nt}^* \mid Adapt)$ is

$$P_{nt}(i_{nt}^* \mid Adapt) = \sum_k (P_{nt}(i_{nt}^* \mid G_k, Adapt) \cdot W_{ntk}'), \qquad (11)$$

where $P_{nt}(i_{nt}^* \mid G_k, Adapt)$ is the probability of choosing i_{nt}^* conditional on goal k given the full-adaptation archetype, and W_{ntk}' is the fully adapted goal weights (see Eq. 4). Note that in Eq. 11 I assume that the choices across scenarios are probabilistically independent.

However, conditional on the no-adaptation archetype, the probability of choosing a choice sequence T_n by consumer n is

$$P_n(T_n \mid NoAdapt) = \sum_k (P_n(T_n \mid G_k, NoAdapt) \cdot W_{nk}), \qquad (12)$$

where W_{nk} is the prior goal weights as specified in Eq. 1, and $P_n(T_n \mid G_k, NoAdapt)$ is the probability of choosing a choice sequence T_n conditional on goal *k* given the no-adaptation archetype. Note that Eq. 12 is different from its counterpart for the full-adaptation archetype (Eq. 10). The reason is that for the full-adaptation archetype goal weights (W_{ntk}') are context-dependent and thus must be integrated into the model at each choice task *t*; whereas for the no-adaptation archetype goal weights (W_{nk}) are context-independent (i.e., a consumer uses the same goal weights throughout all the choice tasks) and thus should be integrated into the model at the consumer level (see Kamakura and Russell 1989). Specifically, for the no-adaptation archetype, the conditional choice probabilities on goal *k* at each choice task *t* should be accumulated within consumer *n*'s choice sequence T_n before the goal weights W_{nk} are accounted for. Thus, $P_n(T_n \mid G_k, NoAdapt)$ in Eq. 12 is specified as

$$P_n(T_n \mid G_k, NoAdapt) = \prod_t P_{nt}(i_{nt}^* \mid G_k, NoAdapt)\,, \tag{13}$$

where $P_{nt}(i_{nt}^* \mid G_k, NoAdapt)$ is the probability of choosing i_{nt}^* at choice task *t* by consumer *n* conditional on goal *k* given the no-adaptation archetype.

Although the ways of integrating goal weights into the model specification are different across the two archetypes, the conditional probability on goal *k* of choosing alternative i_{nt}^* from choice task *t* by consumer *n* is the same, to wit,

$$P_{nt}(i_{nt}^* \mid G_k, Adapt) = P_{nt}(i_{nt}^* \mid G_k, NoAdapt) = \frac{\exp(\overline{A_{ntki_{nt}^*}})}{\sum_{j=1}^{J_{nt}} \exp(\overline{A_{ntkj}})}\,, \tag{14}$$

where $\overline{A_{ntki_{nt}^*}}$ is the systematic component of $A_{ntki_{nt}^*}$, which is the extent to which alternative

i_{nt}^{*} permits attainment of goal k at choice task t for consumer n.

To summarize, the above model specification characterizes the proposed behavioral framework of multiple-goal-based choice (Figure 3-1) and makes the MGBCM (its modeling structure presented in Figure 3-2) fundamentally different from the existing utility-based models. First, the MGBCM positions goals as the core metric of evaluation (see Eq. 2; note that the attribute importance ψ_k is goal-specific). Second, the MGBCM incorporates the interplay between the two underlying behavioral determinants (goal attainments and goal weights) into the model specification (see Eq. 4). Third, the MGBCM also accounts for consumers' tendency to adapt goal weights to the choice context (see Eq. 6). Subsequently I report on tests of the framework and choice model (the MGBCM). Before reporting the results, I describe the data collected in the following section.

3.4 DATA DESCRIPTION

The data were collected through three separate on-line surveys from three different commercial panels drawn from the general Canadian population, restricted to respondents who own at least one point-and-shoot (P&S) digital camera. The purpose of Survey I was to generate a list of goals that consumers might want to pursue when purchasing a P&S camera. Survey II collected data for model estimation and Survey III collected data for an out-of-sample prediction test.

Survey I: Generating a Candidate Goal List for Point-and-Shoot (P&S) Digital Camera

Purchases

One hundred and five individuals from a commercial panel participated in this on-line survey. In the survey a description was first provided to explain to participants what a goal meant (i.e., “when you shop for clothes you might have several goals, like impressing your partner and feeling good about yourself”). They were then asked to write retrospectively about the goals they wanted to achieve when they purchased their currently-owned point-and-shoot digital cameras. Two coders independently content-analyzed the self-reported goals and generated a goal list including both abstract and functional goals as shown in Table 3-1. Inter-coder reliability was 96% and the discrepancies were resolved through discussion between the coders. This goal list was used in the following surveys to assist participants in reporting their goals.

---------------------------Table 3-1 about here------------------------

Survey II: Data for Model Estimation

One thousand eight hundred and ninety individuals from another commercial online panel participated in this second survey. The purpose of this survey was to collect data for model estimation. This survey contained two main parts, (a) goal-related questions and (b) conjoint choice experiments, and the order of the two parts was counter-balanced. A test of the choice responses with an MNL (Multinomial Logit) model shows that there is no significant order effect, so we proceeded with further analyses by pooling all the data. In part (a) participants reported the goals they would pursue while purchasing a new point-and-shoot (P&S) camera by checking the pertinent responses from the above-mentioned goal list. Simple statistics reveal that consumers attempt to pursue multiple goals simultaneously. Specifically, I find that the average number of goals that an individual reports pursuing is 5.3, including 1.5 abstract goals and 3.8 functional goals (see Table 3-2 for the frequencies of self-reported goals). It is important to point out that self-reported goals are *not* used in model estimation but are used to validate the latent constructs captured by the model. In this part of the survey I also asked the participants to state whether, among the goals they had selected, the attainment of one goal was a means of attaining another. By analyzing the responses to this last question, I find that functional goals operate at a lower level in the goal hierarchy as compared to the abstract goals and thus are more likely to predict choice, in line with Construal Level Theory (Trope and Liberman 2010; detailed analysis on goal hierarchy can be found in Appendix 3-1). Therefore I use functional goals for model validation subsequently.

---------------------------Table 3-2 about here------------------------

Part (b) involved a conjoint choice experiment on P&S digital cameras with eight choice tasks for each individual. I employed an entropy-based experimental design with varying choice set sizes (i.e., 2, 4, or 8 alternatives in a choice set). Each camera description used in the design included a full profile of product attributes, with the attribute levels listed in Table 3-3. At the end of the survey, I asked questions about individual characteristics including the usage of, expertise in and investment in P&S digital cameras as well as socio-demographics (see Table 3-4 for the summary statistics on respondent characteristics).

---------------------------Table 3-3 & 3-4 about here------------------------

Survey III: Collecting Data for Out-of-sample Prediction

One thousand and two individuals from a different commercial panel participated in this third on-line survey. The purpose of this survey was to collect independent data for a out-of-sample prediction test. Survey III used the same general structure as Survey II, except that a different experimental design was used for the choice experiment. Specifically, instead of using full profiles of camera attributes, this survey used ten real cameras present in the Canadian market at the time of the survey. Their attribute levels are shown in Table 3-5. I adopted an availability-based design in which I varied, across choice sets, the presence of each camera. The size of choice set also varied (i.e., 4, 5, or 6 alternatives in each choice set), and each participant completed 16 choice tasks. All attributes were held fixed except for price, which was varied by ±20% on the basis of the average market price (rounded to nearest $5). It deserves mentioning that the price range for this second experimental design (i.e., CAN$55- CAN $395) was wider than that for the experimental design used in Survey II (i.e., CAN $79- CAN $259).

---------------------------Table 3-5 about here------------------------

The data used for this out-of-sample prediction test were different from those used for model estimation (see the descriptions about Survey II) in the following aspects: (a) the participants were drawn from a different commercial panel, (b) a different experimental design was used, and (c) the price range was wider. These differences enabled us to conduct a more robust out-of-sample prediction test compared to those commonly used for choice validation.

3.5 ESTIMATION RESULTS

In this section, I first test the proposed behavioral framework (Figure 3-1) by comparing the proposed model (i.e., the Multiple-Goal-Based Choice Model – the MGBCM) with a competing model in terms of the goodness-of-fit and out-of-sample prediction. Next, I provide validation for the latent constructs captured by the MGBCM using self-reported functional goals. Then, I examine the behavior of goal weight adaptation in the sample. Lastly, I discuss the marketing communication strategies suggested by the model parameters.

Goodness-of-Fit

Based on the data collected from Survey II, I estimate the MGBCM and a competing model, a Latent Class Model (LCM) with concomitant variables (e.g., Kamakura, Wedel and Agrawal 1994; Swait 1994). Although it accounts for preference heterogeneity, the LCM is developed from a utility-based perspective that gives goals no explicit roles. Specifically the LCM still conceptualizes *utility* as the core measure for evaluation and ignores the interplay between the underlying behavioral determinants of goal-based choice (i.e., goal weights and goal attainments). As a result, rather than capturing goals, the LCM may only be able to capture latent *preference* classes, which are likely to be based on unknown combinations of latent goals. Given that the LCM is developed on the basis of the utility-based view, the comparison of the MGBCM with the LCM serves as the means of comparing the proposed framework of multiple-goal-based choice (Figure

3-1) with the conventional utility-based conceptualization of choice.

Table 3-6a shows that the MGBCM supports the identification of five latent goals based on the Bayesian Information Criterion (BIC); in contrast, Table 3-6b shows that the LCM identifies four latent preference classes. Comparison of the BIC of the 5-latent-goal MGBCM (38693) with that of the 4-latent-class LCM (38858) shows that that the MGBCM outperforms the LCM by a BIC decrease of 165 points. This result provides initial support for the proposed behavioral framework of multiple-goal-based choice as opposed to the utility-based view on choice.

---------------------------Table 3-6a,b about here------------------------

Out-of-Sample Prediction

I also conduct an out-of-sample prediction test for the MGBCM and the LCM based on the data collected from Survey III. Comparison of the out-of-sample fit of the MGBCM (BIC=41373) with that of the LCM (BIC=43613) shows that the MGBCM outperforms the LCM in the out-of-sample prediction (BIC decrease of 2240 points) much more than in the within-sample goodness-of-fit (BIC decrease of 165 points). This result suggests that the MGBCM can adapt to the changes in data (i.e., a different sample, a different experimental design, and a wider price range) much better than the LCM. Such advantage of the MGBCM over the LCM may be attributed to the fact that the MGBCM allows for goal weight adaptation to the context while the LCM does not. Therefore, this result on out-of-sample prediction provides further support for the proposed behavioral framework (that incorporates goal weight adaptation) as opposed to the utility-based view (that ignores this underlying process). This finding is also consistent with the notion that the model that captures the underlying mechanism makes better prediction especially when changes in the context go beyond the range of historical data (i.e., a wider price range: see Lucas Critique, Lucas 1976).

Validation of Latent Goals

Although the MGBCM outperforms the LCM in both goodness-of-fit and out-of-sample prediction, it would give me greater assurance if I were to find that the latent constructs captured by the MGBCM actually match the self-reported goals observable from the data. Such analyses would provide face validity to the claim that the latent constructs uncovered by the model can be interpreted as goal attainment functions. In this section I use self-reported functional goals to validate the latent constructs captured by the MGBCM. Specifically, I regress the incidence (yes/no) of each of the self-reported functional goals on the estimated latent goal weights calculated from the proposed model. I report in Table 3-7 only the significant positive coefficients (p-value $\leq .05$) from each logistic regression to support the claim of a match (or correlation) between a latent goal and a self-reported functional goal. For example, according to Table 3-7, Latent Goal 1 is associated with the functional goal “keep up with new technology,” while Latent Goal 2 is associated with a combination of four functional goals “have a camera that is easy to carry around”, “have a camera that is easy to use,” “take high quality pictures” and “have a reliable/durable camera.” Table 3-7 shows that each of the latent goals is associated with either a single or a combination of self-reported goals. This suggests that the latent constructs captured by the model are interpretable as goals since the latent constructs are strongly predictive of self-reports.

---------------------------Table 3-7 about here------------------------

In the next section, I interpret the estimates of the MGBCM to answer the following questions: how do consumers adapt goal weights to the context (Part I of Table 3-8); what goals are pursued by consumers and how important are they (Part II of Table 3-8); how are product attributes evaluated with respect to goals (Part III of Table 3-8); how do consumers set prior goal weights (Part IV of Table 3-8).

Goal Weight Adaptation

In this section I focus on examining which factors influence the tendency to adapt, what is the overall tendency to adapt in the sample and how consumers in the sample adapt their goal weights across choice situations. I find that, in Part I of Table 3-8, the coefficients for SLR and frequency of taking photography trips (i.e., the two indicators of objective expertise) are significant and negative. This suggests, as predicted, that having greater objective expertise leads to a higher tendency to adapt. Although I do not find support for the other prediction I made (i.e., that consumers with more subjective expertise have greater tendency not to adapt), I find that subjective expertise has no effect on the tendency to adapt as the parameter for self-reported expertise is not significant. To summarize, the results show that it is objective expertise, rather than subjective expertise, that may increase consumers' tendency to adapt.

---------------------------Table 3-8 about here------------------------

I also find that on average the tendency to adapt in the sample is about 0.2, on the possible scale [0,1]. To examine the distribution of this adaptation tendency measure, I divide the sample into three subgroups: 1) *high adapters* whose tendency to adapt is greater than 0.7, 2) *balanced adapters* whose tendency to adapt is between 0.3 and 0.7, and 3) *low adapters* whose tendency to adapt is lower than 0.3. The percentage of the three subgroups in the sample is that 9% for high adapters, 16% for balanced adapters and 75% for low adapters.

To further understand how each subgroup adapts their goal weights across choice scenarios, I calculate the goal weights for each of the eight choice scenarios, averaged over consumers within each subgroup. I find as expected that low adapters hardly adapt any goal weights across choice situations; interestingly, however, the high and balanced adapters show different patterns of adaptation with respect to different goals. Specifically, high and balanced adapters hardly make any adaptation with respect to Latent Goal 1, 2, 5 but make significant adaptation with respect to Latent Goal 3 and 4 (see Figure 3-3a and b). This suggests that goal weight adaptation depends not only on consumers but also on the specific goals.

--------------------------Figure 3-3a,b about here-----------------------

A possible explanation for why high and balanced adapters adapt LG3 and LG4 instead of the other goals may be that LG3 and LG4 are much more sensitive to the context than the other goals. This explanation is supported by the estimates of the goal scales. As shown in Part II of Table 3-8, the scales of LG3 and LG4 (0.103 and 0.083 respectively[2]) are both significantly smaller than the root scale that is normalized at one

[2] The estimated natural logarithms of these scales are -2.274 and -2.489, respectively, as shown in Part II of Table 3-8.

whereas the scales of the other goals are not significantly different from the root scale.[3] Since smaller goal scales indicate greater sensitivity to the choice context, the estimates of the goal scales suggest that LG3 and LG4 are more sensitive to the influence from the context as compared to the other latent goals (i.e., LG1, LG2, LG5). Understanding goals' sensitivity to the choice context is important, as such insights may guide marketers to invest more resources in influencing certain consumers' goals via marketing programs.

Latent Goals and Their Importance (i.e., Adapted Goal Weights)

The estimation results show that consumers pursue five latent goals, which are strongly associated with either a single or a combination of self-reported goals (see Table 3-7). Based on Table 3-7, I suggestively label the latent goals (LG1-LG5) in terms of the associated self-reported goals in Part II of Table 3-8.

The average importance (i.e., adapted goal weight) of the five latent goals is 13%, 22%, 21%, 21%, 23%, respectively, in the estimation sample (data collected from Survey II). This suggests that there are no dominant latent goals and that it might be risky for marketers to ignore any of them in developing marketing programs. However, by examining the average goal importance for each of the three subgroups (i.e., high adapters, balanced adapters and low adapters), I find that the goal weights become more concentrated toward the Latent Goal 4 and 5 as consumers' tendency to adapt increases (see Figure 3-4). Specifically, low adapters seem to spread goal weights evenly across all five goals; balanced adapters mainly pursue three latent goals, LG2, LG3 and LG4, with

[3] During estimation the goal scales of LG1, LG2 and LG5 are fixed at one, that is, their natural logarithms are fixed at zero. This is an empirically determined restriction that does not impact our results.

the weights of 21%, 26% and 37% respectively; high adapters focus predominately on two latent goals, LG3 and LG4, with the weights of 26% and 63% respectively. This suggests that for the consumers with greater tendency to adapt goal weights (i.e., possibly those with greater objective expertise) it may be more effective to emphasize in promotional material the pursuit of LG3 (which is associated with the self-reported goal of "taking good quality pictures") and LG4 (which is associated with the self-reported goal of "keeping up with new technology").

---------------------------Figure 3-4 about here------------------------

Attribute Importance to Goal Attainment, Prior Goal Weighting and Marketing Communications

As previously discussed, one of the contributions made by the MGBCM is that this model can separate attribute importance to goal attainment (ψ_k of Eq. 2) from goal importance (W_{ntk}' of Eq. 4), the two constructs that are confounded by utility-based models. In this section, I focus on discussing how the separation of these two constructs provides insights into consumer behavior and thus helps improve marketing communication strategies.

Apart from goal importance as discussed in the previous section, the MGBCM can separately estimate the attribute importance to goal attainment as reported in Part III of Table 3-8. These estimates, together with the estimates reflecting the impact of individual characteristics on prior goal weighting (γ_k of Eq 1, 4; see Part IV of Table 3-8), may help marketers develop innovative positioning, advertising and positioning strategies. Thus, based on the corresponding model estimates reported in Table 3-8, I present Table 3-9, which summarizes (a) the attributes that are considered as contributing to the attainment of each goal (based on Part III of Table 3-8) and (b) the corresponding consumer profiles (based on Part IV of Table 3-8).

--------------------------Table 3-9 about here-----------------------

Based on Table 3-9, marketers can position their products around the goal(s) which their brand is best at achieving, focus on advertising the attributes contributing to the attainment of the goal(s), and target the consumers who are predisposed to assign greater weights to the goal(s). For example, marketers of the Sony brand can position their cameras around the goal of “have a reasonably-priced camera that is easy to use” (i.e., Latent Goal 5); focus on advertising the attributes of high zoom, small camera size, water proof functionality and low price; and target novices who use cameras occasionally for family/friends gatherings and who are not willing to spend too much money on cameras. Due to the limitation of space, I provide more detailed discussions in Appendix 3-2 about how Table 3-9 can be used to guide the positioning, advertising and targeting strategies for each brand in the data (i.e., Canon, Panasonic, Sony and Fujifilm).

Note that the two latent goals, LG1 and LG4, are both related to the self-reported goal “keep up with new technology” and that different attributes are considered as contributing to this same self-reported goal (see Table 3-8 and 3-9). This may suggest that there exist two sub-groups of people who evaluate the self-reported goal (i.e., keep up with new technology) in different ways. Stated differently, there might exist heterogeneity in evaluation for each goal. I leave the investigation of this question to future research.

Table 3-9 can also help marketers to develop effective product design strategies. The general principle is that a new product is more desirable if it bears the features that contribute to achieving the goals with which the brand is strongly associated. In the next section, I show how the proposed model (the MGBCM) can help design *specific* attribute levels for new products.

3.6 POLICY ANALYSIS

New product designs require the knowledge of consumers' willingness to pay (WTP) for a certain change in a product attribute (e.g., increasing resolution from 12 to 14 megapixels, adding the feature of high-speed burst-shooting). In this section, I compare WTP computed on the basis of the proposed goal-based model (the MGBCM) and the competing utility-based model (the LCM) respectively. The purpose of the comparison is to assess the value of the proposed model in assisting marketing policy decisions related to the product.

I compute WTP for two conditions: changes in the product attributes that are continuous variables (e.g., resolution, zoom and LCD size) are either (a) within or (b) outside the range of the corresponding variables in the data for estimation (see details in Appendix 3-3). For example, given that the range of resolution in the data used for estimation is 10-16 megapixels (see Table 3-3), I change resolution from 12 to 14 megapixels in condition (a) but change it from 16 to 18 megapixels in condition (b). The purpose of having the two conditions is to test a prediction made on the basis of Lucas Critique (Lucas 1976): ignoring the interplay between the underlying behavioral determinants (as is the case for the LCM) is more likely to produce unreliable policy predictions when the attribute changes used for policy prediction go beyond the corresponding variation in the data used for model estimation.

The predicted results for the two conditions are shown in Figures 3-5a and b respectively. As the MGBCM describes goal-based choice processes consistent with behavioral theories, fits the data better, predicts better on a hold-out sample and has its latent constructs validated as goals, this model (the MGBCM) is likely to be a better representation of consumer choice and hence the WTPs computed on the basis of it are likely to be more reliable. Figure 3-5a and b show that there exist significant differences, in both magnitude and ordering, between the WTPs computed from the MGBCM and those from the LCM. Such differences may suggest that the utility-based LCM may not be reliable in providing policy predictions. For example, marketers relying on the LCM over the MGBCM may overestimate the WTP for increasing resolution (i.e., from 12 to 14 mega pixels) by 70% but underestimate the WTP for adding touch screen functionality by 35%.

--------------------------Figure 3-5a,b about here-----------------------

I also find as predicted that the differences between the WTPs computed from the two models are greater in condition (b) than in (a) (see Figure 3-5a, b). For example, as compared to the MGBCM, the LCM overestimates the WTP for increasing zoom from 8 to 12 times by 26% in condition (a) but 425% in condition (b); the LCM also overestimates the WTP for increasing resolution from 12 to 14 mega pixels by 70% in condition (a) but 100% in condition (b). These findings suggest that the LCM is even more unreliable in making policy predictions when the context used for policy analyses varies significantly from the context used for model estimation, since the LCM does not characterize the underlying behavioral mechanism of goal-based choice and thus is unable to adapt to the variation of the context.

3.7 GENERAL DISCUSSION

As previously discussed, the results from this research have provided support for the proposed framework (Figure 3-1) and choice model (the MGBCM). Since a major difference between the MGBCM and the utility-based LCM lies in whether goal weight adaption is incorporated, I surmise that as the tendency to adapt increases the LCM is more likely to be outperformed by the MGBCM due to the decreased capability of the LCM to capture goals. I speculate that in extreme case where tendency to adapt is 100% (i.e., consumers fully adapt goal weights to the context), the LCM completely fails to capture goals and thus produces biased model parameters. To test this speculation I conducted a Monte Carlo Simulation study (see Appendix 3-4 for a detailed description). I estimate both the MGBCM and the LCM upon data sets in which individuals *fully adapted* their prior goal weights to the context. The results show that the LCM can neither recuperate the true number of goals nor the true goal-specific attribute importance parameters (i.e., ψ_k in Eq. 2; see results in Appendix 3-4). This finding supports the speculation that ignoring goal weight adaption when it exists prevents any choice model from capturing goals and thus produces biased parameters for goal-specific attribute importance.

On the other hand, as shown by the previous results the MGBCM is likely to capture goals,[4] which *determine* taste classes in the sense that different taste classes are formed to reflect different combinations of goals. Since goal combinations (i.e., goal weighting) are context-dependent as previously discussed, taste classes are also likely to be context-dependent. This challenges the conventional assumption underlying the taste heterogeneity models: *taste* does not change within individual regardless of context (e.g., Kamakura and Russell 1989; McFadden and Train 2000). In fact, a few studies have already provided empirical support for context-dependent taste heterogeneity by showing that a consumer varies his/or her taste with, for example, motivational states (Yang, Allenby and Fennell 2002), usage occasions (Desarbo et al. 2008; Lee, Sudhir and Steckel 2002) and social groups/context scenarios (Kim and Chintagunta 2012). Although these studies concentrate on describing how *taste* varies with context, the current research focuses on capturing the underlying *drivers* for the variation, the goals, which explain the existence of both within- and between-individual taste heterogeneity.

3.8 CONCLUSION AND FUTURE RESEARCH

This research proposes, models, and tests a framework of simultaneous multiple goal pursuit in consumer product choice (Figure 3-1). The framework incorporates three key components: prior goal weighing, goal-specific attribute evaluation and goal weight adaptation. The results show for the data that the proposed model (the Multiple-Goal-Based Choice Model - MGBCM) outperforms the utility-based Latent Class Model (the LCM) in both goodness-of-fit and out-of-sample prediction, providing empirical support

[4] I have shown previously that the MGBCM describes goal-based choice processes consistent with behavioral theories, fits the data better, predicts choice better on a hold-out sample and has its latent constructs validated as goals.

for the proposed framework. I also discuss the insights provided by the proposed model in terms of formulating effective targeting, positioning and advertising strategies. Finally, the results from the policy analyses show that the MGBCM predicts quite different WTP measures than the LCM, suggesting that the LCM may not be reliable in making policy predictions, given that the MGBCM describes a decision-making process more consistent with the behavioral theories, fits the data better and predicts better on a hold-out sample.

The contribution of this research is three-fold. First, I propose a new goal-based conceptualization of choice as opposed to the conventional utility-based view. This new conceptualization cannot be incorporated by the utility-based view since it omits the interplay between the underlying behavioral determinants of goal-based choice. The consequence of such omission may lead to inaccurate policy predictions (see Lucas Critique, Lucas 1976). Second, I advance choice modeling by developing a new choice model on the basis of the goal-based conceptualization of choice. Not only does this new model predict better, but also it separates the two distinct constructs (goal importance and attribute importance to goal attainment) that are confounded in the *preference* parameters of the utility-based model. The separation of the two constructs provides additional insights into consumer behavior that help improve marketing communication strategies. Third, I extend the existing behavioral theories on goal-based choice by allowing for within-choice goal adjustment. Although the existing behavioral studies in goal-based choice mainly focus on goal revision across different choice scenarios, the results from the current research show that consumers may adapt their prior goal weights based on goal attainability of a given choice context. Such extension is theoretically important as it reflects the interplay of joint top-down and bottom-up processes within a single choice

(Weber and Johnson 2009).

One limitation of the present research is that it assumes that there is no heterogeneity in attribute importance to goal attainment (ψ_k in Eq. 2). It is likely that different consumers view attribute importance to the same goal differently. Indeed, the proposed model finds in the digital camera choice data that there seems to exist two groups of people each of whom uniquely map attributes to the same self-reported goal of "keeping up with new technology." However, I treat the two mapping schemes as two different latent goals. It might be more conceptually coherent if heterogeneity in goal-specific attribute importance were incorporated within latent goals. Adding an additional layer to the model significantly increases model complexity, since a priori the number of goals and the number of different mapping schemes conditional on each goal are unknown. I leave the pursuit for this extension to future research.

Recognizing the role of goals in consumer choice opens up many promising avenues for future research. First, as previously discussed the latent goal scales (the μ_k's) of the proposed model can reflect the sensitivity of goals to the context. It is also possible that such sensitivity is related to goal commitment. In future research a combination of the behavioral methods and modeling can be used to further examine the capability of the proposed model to capture this important behavioral construct.

Second, future research can also examine how goals influence choice set formation. Specifically, consumers may have certain thresholds for goal attainment, and only the alternatives that can help attain the goals over and above the thresholds are considered for choice. Incorporating such goal-based thresholds into the model specification extends the existing choice set formation models (e.g., Swait and Ben-Akiva 1987a,b). It would also be interesting to examine different patterns of goal-based choice set formation (for instance, using relatively low thresholds for all goals vs. using a relatively high threshold for a single important goal) and to investigate whether the selection of these patterns is influenced by general goal orientation (i.e., prevention-focused vs. promotion focused, Higgins 2000).

Next, multiple “goal operators” also deserve examination in future research. In the present work, the proposed model employs maximization as the only goal operator to evaluate goal attainment, suggesting that decision makers want to achieve all goals by pursuing them to the highest extent possible. However, goals might also be deemed as attained upon meeting a threshold, referred to as “satisficed” (Simon 1955). It is likely that rather than striving to maximize all goals, consumers attempt to maximize some important goals while satisficing other less important goals. Therefore, it would be interesting to incorporate satisificing as an alternative goal operator without assuming a priori which goals are maximized or satisficed.

Finally, modeling goal hierarchy is another important endeavor for future research, as such models may better characterize goal-driven choice processes and thus be able to make better predictions and provide more insightful directions for marketing strategies. The main challenge of such a venture is that the number of hierarchy levels, the number of goals at each level, and the association between higher- and lower-level goals are all unknown to researchers. Therefore, it might be helpful to identify certain “archetype” goal structures under controlled environments and then “mix” them in the modeling of uncontrolled consumer choice behavior. Despite the difficulties, modeling goal hierarchy is definitely an important extension to understanding and modeling multiple-goal-based choice.

3.9 TABLES

Table 3-1 Goal List Generated From Survey I

Abstract Goals	acquire skills in photography
	record memory
	have fun taking pictures
	make me look good to others, including family, friends and strangers
Functional Goals	keep up with new technology
	have a camera that is easy to carry around
	have a camera that is easy to use
	take good quality pictures
	minimize how much I spend on cameras
	have a reliable/durable camera

Table 3-2 Frequencies of the Self-reported Goals in Survey II

		#of people reporting the goal	Percentage of the Sample
Abstract Goals	acquire skills in photography	382	20%
	record memory	1174	62%
	have fun taking pictures	1072	57%
	look good to others	225	12%
	average	***713.25***	***38%***
Functional Goals	keep up with new technology	520	28%
	have a camera that is easy to carry	1326	70%
	have a camera that is easy to use	1451	77%
	Take good quality pictures	1630	86%
	minimize spending on cameras	757	40%
	have a reliable/durable camera	1485	79%
	average	***1194.83***	***63%***

Table 3-3 Attribute Levels Used in Experimental Design for Survey II

Camera Attributes	Levels
Brand	Panasonic/Sony/Fujifilm/Canon
Price ($)	79/139/199/259
Resolution (megapixel)	10/12/14/16
Zoom (times)	4/8/12/16
High-speed Burst Shooting	no/yes
Touch Screen	no/yes
LCD Size (inch)	2.7/3/3.3/3.6
Camera Size	pocket size/compact case needed
Water Proof	no/yes
Easy upload for Facebook	no/yes

Table 3-4 Summary Statistics of Individual Characteristics for Survey II

Variable Name	Mean	Std Dev	Min	Max
Camera Usage/Expertise Variables				
UseFreqency (How frequently do you use your P&S camera? 1: once a year or less; 6: daily)	4.13	1.26	1	6
Occasion (For which occasion do you use your P&S camera most often?)				
Family	0.49	0.50	0	1
Friends	0.15	0.36	0	1
Vacation	0.23	0.42	0	1
SpecialTrip(trips made specifically for photography)	0.03	0.18	0	1
Other (used as base level)				
TripFreqency (How frequently do you make trips specifcially to photograph something or someone besides your family? 1: never; 6: at least once a week)	3.13	1.68	1	7
CameraCost (How much did you spend on your current P&S camera?)	204.43	96.78	50	425
Camera# (In the past ten years, how many P&S cameras have your purchased for your self?)	2.00	1.01	1	5
SLR (Do you currently own a SLR? 0: no; 1: yes)	0.26	0.44	0	1
CameraExpertise (I know a lot about cameras; I could talk about cameras for a long time; I am very familiar with cameras.1: strongly disagree; 7: strongly agree)	3.79	1.43	1	7
Demographics				
Gender(1:male;2:femail)	1.52	0.50	1	2
Age	42.48	14.42	2	85
Education (1: less than high school; 7: graduate degree)	4.37	1.21	1	7
Income (Annual Household Income $)	63808.44	31710.61	17500	130000

Table 3-5 Ten Real Cameras Used in the Choice Experimental Design of Survey III

Camera	1	2	3	4	5	6	7	8	9	10
Model	DMC-S1	DMC-TS10	DMC-FH27	DMC-ZS10	Cybershot DSC-W510	Cybershot DSC-W370	Cybershot DSC-TX10	Fujifilm JV100	FinePix XP20	FinePIx Z900 EXR
Brand	Panasonic	Panaso nic	Panaso nic	Panaso nic	Sony	Sony	Sony	Fujifilm	Fujifilm	Fujifilm
Price ($)	99	159.95	184.95	289	99.95	139.95	329.99	69.95	164.99	249
Resolution (megapixel)	12	14.1	16	14.1	12	14	16	12	14	16
Zoom (times)	4	4	8	16	4	7	4	3	5	10
High-speed Burst Shooting	no	no	yes	yes	no	yes	yes	no	no	yes
Touch Screen	no	no	yes	yes	no	no	yes	no	no	yes
LCD Size (inch)	2.7	2.7	3	3	2.7	3	3	2.7	2.7	3.5
Camera Size	pocket size	compact case needed	compact case needed	compact case needed	pocket size	compact case needed	pocket size	pocket size	compact case needed	pocket size
Water Proof	no	yes	no	no	no	no	yes	no	yes	no
Easy upload for Facebook	yes	no	yes	yes	yes	yes	yes	no	yes	yes

Table 3-6 Selection of the Optimum Number of Latent Constructs

a) The Multiple-Goal-Based Choice Model (the MGBCM)

Model	k	LL	BIC
2-Latent-Goal Model	52	-19316	39132
3-Latent-Goal Model	84	-19036	38880
4-Latent-Goal Model	116	-18822	38761
5-Latent-Goal Model	**146**	**-18644**	**38693**
6-Latent-Goal Model	177	-18504	38712

Note: 1. k is the number of parameters.

2. LL is the log-likelihood value.

3. BIC refers to Bayesian Information Criterion

b) The Utility-Based Latent Class Model (the LCM)

Model	k	LL	BIC
2-Latent-Class Model	47	-19389	39230
3-Latent-Class Model	78	-19105	38961
4-Latent-Class Model	**109**	**-18904**	**38858**
5-Latent-Class Model*	140	-18686	38720
6-Latent-Class Model	171	-18558	38762

*This model is not selected as the optimum model because a latent class of this model is poorly determined, that is, the size of this latent class is only 2% and the estimated standard errors for attribute importance are very large.

Table 3-7 Association Between Latent Goals and Self-reported Functional Goals

Latent Goals	Self Reported Functional Goals					
	keep up with new technology	have a camera that is easy to carry	have a camera that is easy to use	take good quality pictures	minimize spending on cameras	have a reliable /durable camera
LG1	0.496					
LG2		1.075	0.739	1.053		0.766
LG3				0.800		
LG4	0.657					
LG5			0.872		1.581	

Table 3-8 Parameter Estimates of the Multiple-Goal-Based Choice Model (the MGBCM)

Part I: Goal Weight Adaptation	Adaptation	No-adaptation
TripFrequency	0	-1.162(0.42)***
SLR	0	-0.293(0.102)***
CameraExpertise	0	0.085(0.422)

Part II: Identified Latent Goals (LG)

Latent Goal	LG1 (13%)	LG2 (22%)	LG3 (21%)	LG4 (21%)	LG5 (23%)
StronglyAssociated Self-Reported Goal	Keep up with new technology	Have a camera that is easy to carry/ Have a camera that is easy to use/ Take good quality pictures/ Have a reliable or durable camera	Take good quality pictures	Keep up with new technology	Have a camera that is easy to Use/ Minimize spending on cameras
ln(GoalScale)	-- fixed at 0--	-- fixed at 0--	-2.274(0.224)***	-2.489(0.197)***	-- fixed at 0--
Part III: Goal-Specific Attribute Evaluation					
Panasonic	-0.558(0.092)***	0.133(0.051)***	0.041(0.063)	-0.187(0.123)	-0.101(0.045)**
Sony	0.758(0.075)***	0.024(0.045)	0.056(0.066)	0.084(0.103)	0.289(0.038)***
Fujifilm	-1.699(0.142)***	-0.221(0.049)***	-0.424(0.067)***	-0.696(0.117)***	-0.134(0.045)***
Price(L)	-0.224(0.103)**	-0.025(0.089)	-0.105(0.109)	0.744(0.168)***	-0.79(0.074)***
Resolution(L)	0.084(0.097)	-0.032(0.086)	0.317(0.11)***	0.211(0.165)	0.037(0.063)
Zoom(L)	0.15(0.1)	0.05(0.087)	0.683(0.123)***	0.28(0.165)*	0.108(0.064)*
BurstShooting	0.013(0.106)	0.206(0.087)**	0.156(0.113)	0.169(0.171)	-0.011(0.067)
TouchScreen	0.077(0.101)	0.138(0.085)	-0.131(0.105)	0.075(0.164)	0.008(0.07)
LCDSize(L)	0.005(0.1)	-0.087(0.087)	-0.048(0.108)	0.129(0.167)	-0.084(0.065)
CameraSize	-0.432(0.106)***	-0.269(0.093)***	0.053(0.113)	-0.131(0.17)	-0.217(0.062)***
WaterProof	0.057(0.107)	0.793(0.099)***	0.213(0.111)*	0.035(0.171)	0.151(0.067)**
FacebookUpload	0.091(0.102)	0.082(0.09)	-0.073(0.114)	0.168(0.164)	-0.027(0.07)
Price(Q)	-0.324(0.044)***	-0.304(0.032)***	-0.241(0.04)***	-0.341(0.084)***	-0.192(0.052)***
Resolution(Q)	-0.05(0.047)	0.023(0.032)	-0.008(0.05)	0.098(0.082)	0.01(0.032)
Zoom(Q)	-0.087(0.041)**	-0.052(0.032)	-0.202(0.061)***	0.18(0.076)**	-0.058(0.029)**
LCDSize(Q)	0.059(0.044)	0.008(0.032)	0.018(0.04)	0.04(0.072)	-0.038(0.033)

(Continued)

Table 3-8 (cont.)

Part IV: Impact of Individual Characteristics on Prior Goal Weighting

UseFrequency	-- fixed at 0--	-0.308(0.401)	0.52(0.448)	-0.488(0.579)	-1.109(0.414)***
Family	-- fixed at 0--	0.113(0.22)	-0.532(0.216)**	0.126(0.268)	-0.04(0.226)
Friends	-- fixed at 0--	-0.185(0.285)	-0.623(0.294)**	-0.744(0.365)**	-0.309(0.285)
Vacation	-- fixed at 0--	0.646(0.3)**	0.505(0.299)*	0.533(0.374)	0.402(0.301)
SpecialTrip	-- fixed at 0--	-0.721(0.588)	0.477(0.468)	-0.146(0.643)	-0.594(0.615)
TripFrequency	-- fixed at 0--	-0.189(0.733)	-0.484(0.779)	0.767(0.892)	-0.632(0.783)
CameraCost	-- fixed at 0--	-0.773(0.483)	0.651(0.486)	2.009(0.639)***	-3.826(0.533)***
Camera#	-- fixed at 0--	1.272(0.471)***	0.096(0.519)	0.484(0.659)	0.343(0.504)
SLR	-- fixed at 0--	0.055(0.139)	0.25(0.144)*	-0.223(0.184)	-0.215(0.154)
CameraExpertise	-- fixed at 0--	-0.934(0.591)	0.605(0.643)	1.296(0.751)*	-1.35(0.588)**
Gender	-- fixed at 0--	-0.028(0.121)	-0.051(0.129)	-0.074(0.158)	-0.295(0.121)**
Age	-- fixed at 0--	0.016(0.686)	0.429(0.756)	-1.107(0.971)	0.287(0.697)
Education	-- fixed at 0--	-1.062(0.633)*	-1.12(0.642)*	-0.396(0.849)	0.477(0.634)
Income	-- fixed at 0--	-0.662(0.43)	-0.211(0.467)	0.933(0.559)*	-0.508(0.437)
Constant	-- fixed at 0--	0.414(0.224)*	0.335(0.212)	-1.184(0.299)***	0.07(0.237)

Note: 1. In the parentheses are the standard errors."*" refers to 0.05<p-value≤0.1; "**"0.01<p-value≤0.05;"***"p-value≤0.01.

2. (L) means the linear term of the variable, (Q) means the quadratic term of the variable.

Table 3-9 Goals, Valued Attributes With Respect To (w.r.t.) the Goal, & Consumer Profiles

	Positioning	**Advertising**	**Targeting**
Latent Goals	**Strongly Associated Self-Reported Goal(s)**	**Valued Attributes w.r.t. the Goal**	**Consumer Profiles**
LG1	**Keep** up with new technology	**C**anon*/Sony; **S**mall camera size; **L**ow price	**Use** cameras mainly for family/friend occasions
LG2	**Have** a camera that is easy to carry; **Have** a camera that is easy to use; **Take** good quality pictures; **Have** a reliable or durable camera	**P**anasonic/Canon; **B**urst shooting; **S**mall camera size; **W**ater proof; **M**edium price*	**Use** cameras mainly for family/friends occasions and for vacations; **Bought** more number of cameras previously
LG3	**Take** good quality pictures	**C**anon; **H**igh resolution; **H**igh zoom; **W**ater proof; **L**ow price	**Use** cameras mainly for vacations; **Own** a SLR currently
LG4	**Keep** up with new technology	**C**anon; **H**igh zoom; **H**igh price	**Use** cameras mainly for family occasions; **Spent** more money on the currently-owned P&S camera; **High** level of expertise
LG5	**Have** a camera that is easy to use; **Minimize** spending on cameras	**S**ony; **H**igh zoom; **S**mall camera size; **W**ater proof; **L**ow price	**Use** cameras mainly for family/friends occasions; **Use** cameras infrequently; **Spent** less money on the currently-owned P&S camera; **Low** level of expertise

Notes:

*Brand is effects-coded normalized on Canon, so the brand-specific coefficient for Canon is the negative of the sum of the other three brand-specific coefficients.

*The quadratic effect of price has been taken into account.

3.10 FIGURES

Figure 3-1 The Framework of Simultaneous Multiple Goal Pursuit in Product Choice

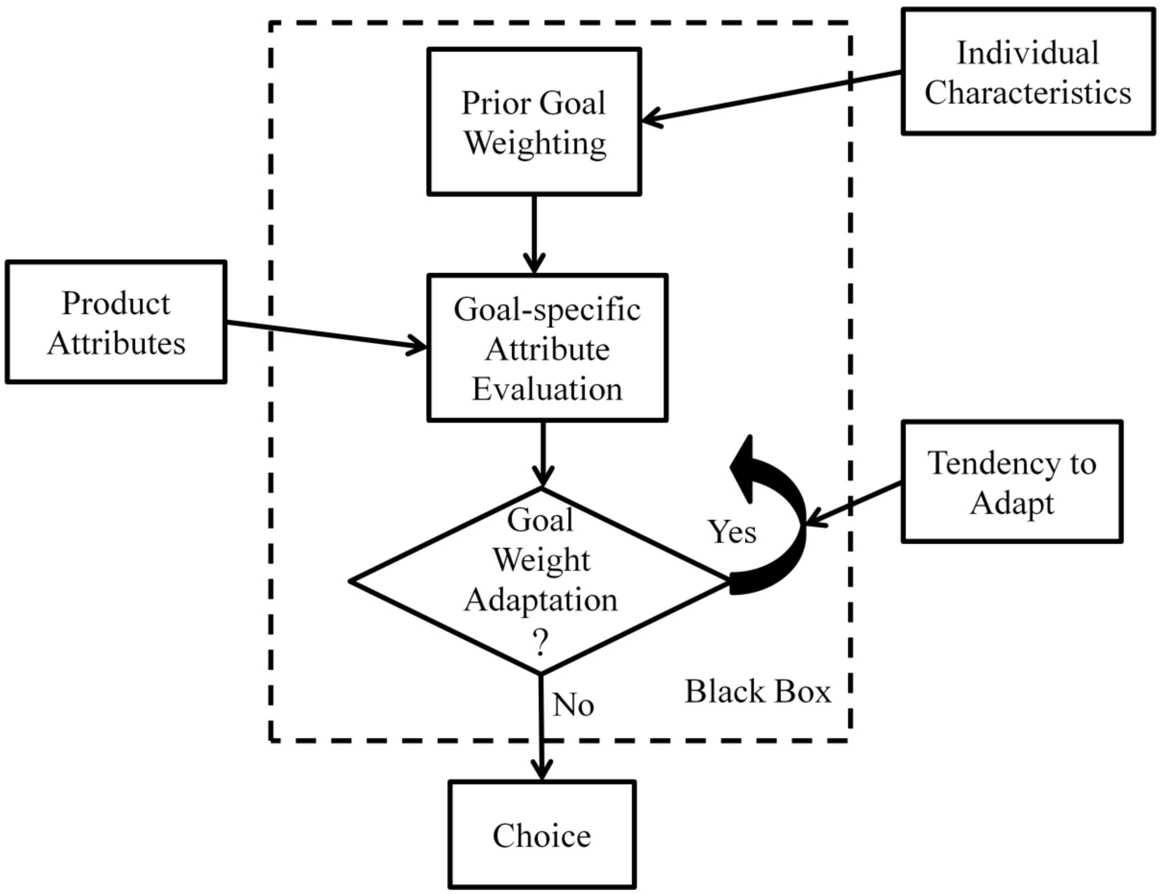


Figure 3-2 The Modeling Structure of Multiple-Goal-Based Choice Model (MGBCM)

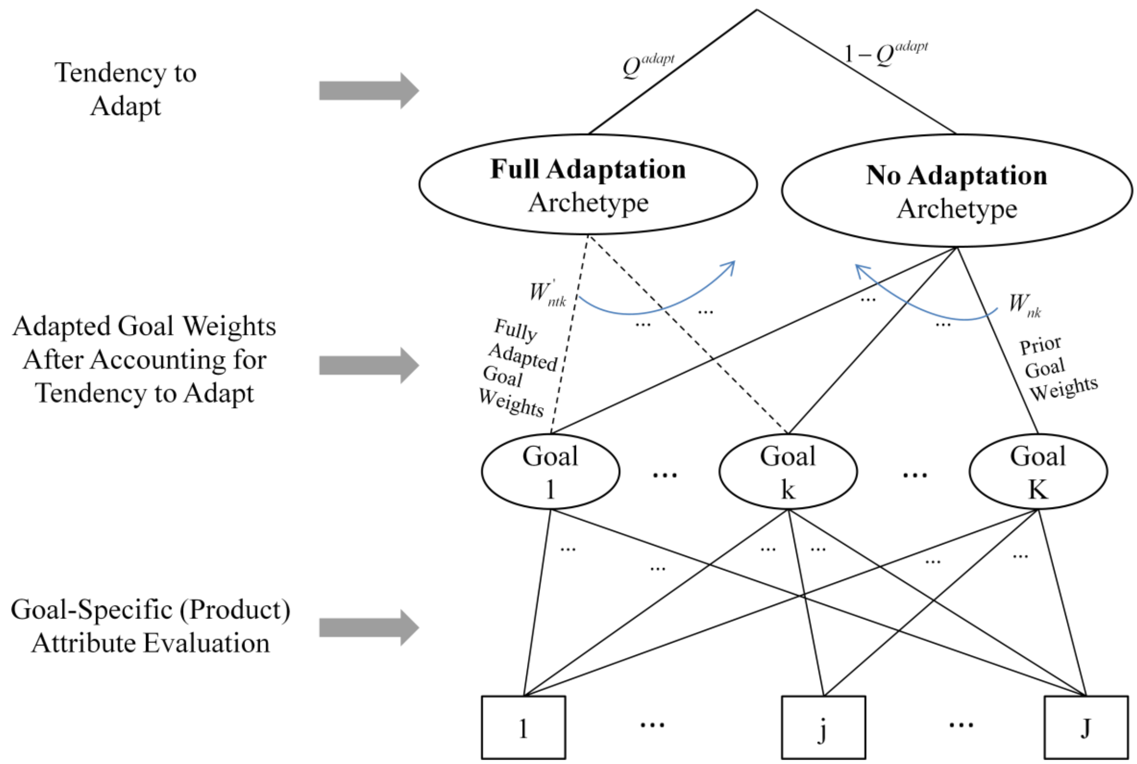
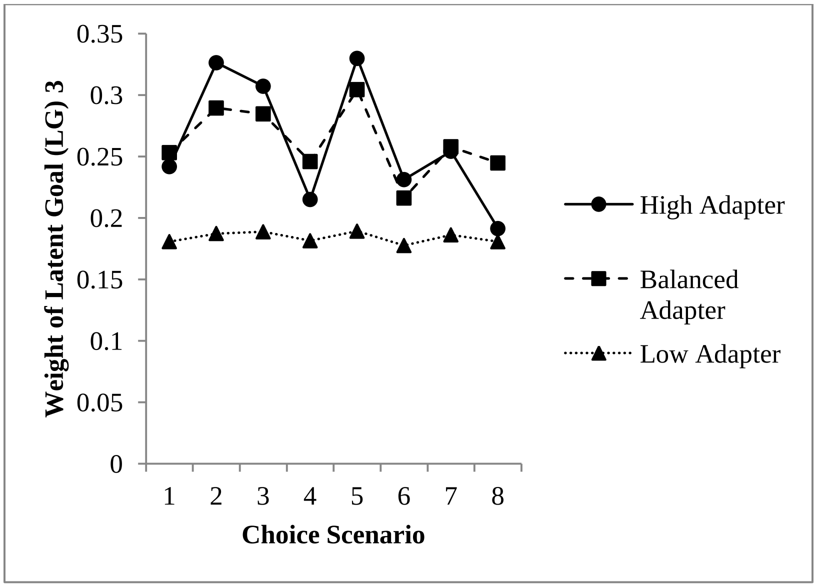


Figure 3-3 Variation of Latent Goal Weights Across Choice Scenarios

(a) Variation of Latent Goal 3's Weight Across Choice Scenarios



(b) Variation of Latent Goal 4's Weight Across Choice Scenarios

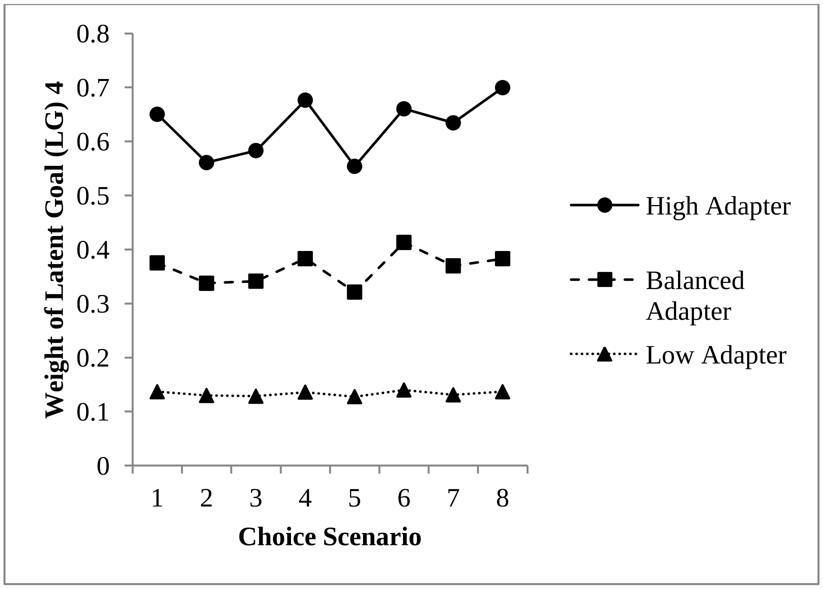


Figure 3-4 Comparing Goal Weight Allocation Across High Adapter, Balanced Adapters and Low Adapters

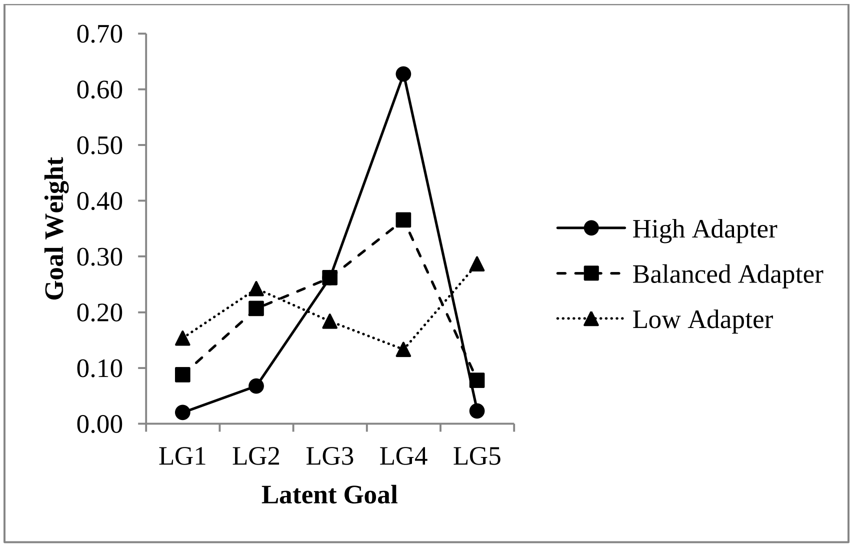
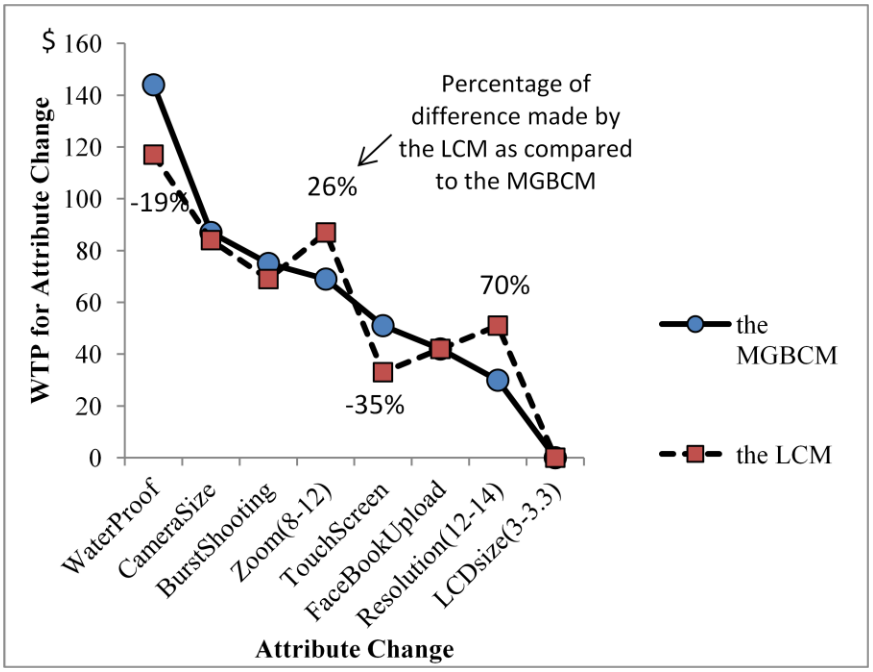
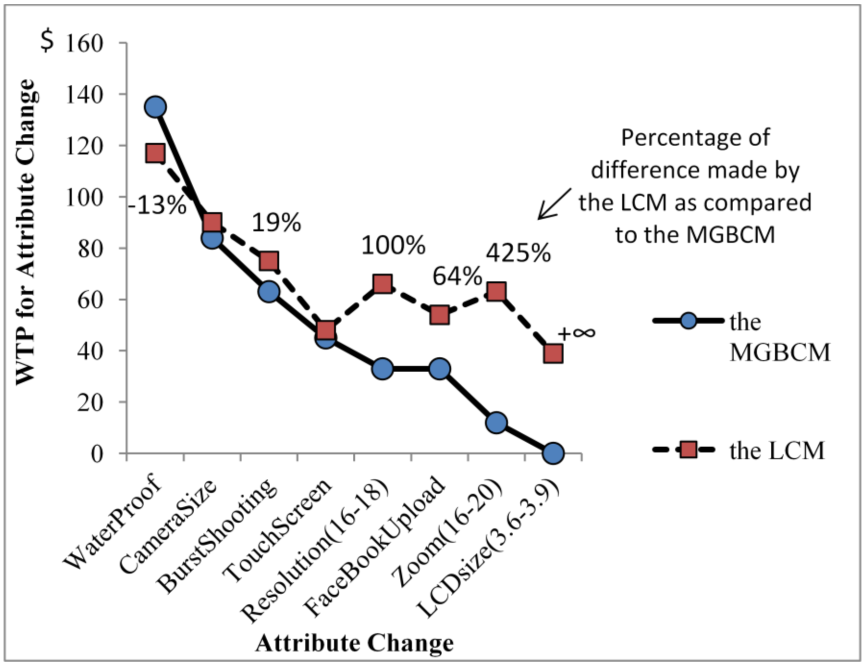


Figure 3-5 Policy Analysis Based on the Multiple-Goal-Based Choice Model (the MGBCM) VS. the Latent Class Model (the LCM)

(a) Attribute Changes Used in Policy Analyses are Within the Corresponding Ranges in the Data Used for Model Estimation



(b) Attribute Changes Used in Policy Analyses Go Beyond the Corresponding Ranges in the Data Used for Model Estimation



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4. CONCLUSION

This thesis contains two essays that respectively examine the role of two forms of antecedent volition (i.e., replacement strategy and multiple activated goals) in decision processes. The results of the first essay suggest that, in replacement decisions of consumer durables, a process of selecting a replacement strategy (i.e., making the higher-order decision on whether to replace or not) exists prior to evaluation, which is made with respect to the reference points (the incumbent product) and is conditional on the preceding replacement strategy selection (expressed as a choice set formation process revolving around the incumbent product). The results from the second essay suggest that (a) consumers bring previously activated goals to choice situations, and it is with respect to these goals that products are evaluated; (b) they also adapt goal weights to the actual goal attainability of a choice scenario by assigning greater weight to more attainable goals, which is thus shown to be a source of context adaptation.

The contribution of the thesis is three-fold. First, it shows the importance of treating antecedent volitional stages as a (descriptive and modeling) part of consumer decision processes. Specifically, the two forms of antecedent volition (replacement strategy and goals) are shown to play critical roles in consumer decision-making. On the one hand, antecedent volition directs consumer evaluative processes: new products are evaluated conditional on choosing the replacement strategy vs. the no-replacement strategy; products are evaluated with respect to specific activated goals, not some general attractiveness measure (i.e., products are attractive because they enable goal attainment). On the other hand, pre-evaluation volition interacts with choice context: replacement strategy selection depends on the overall attractiveness of the replacement assortments presented in a choice scenario; pre-determined goal weights are adapted to the actual goal attainability of a choice situation. Incorporating these roles of antecedent volition into a broad picture of decision process provides greater insight into consumer choice behavior.

Second, the thesis develops new choice model specifications that incorporate the two particular forms of antecedent volition. These new models are adaptive in the sense that they depict decision makers as anchoring-and-adjusting on stable and adaptable evaluation modes. As compared to conventional models, these new choice models describe consumer decision processes more consistently with behavioral theories, fit the data better and thus are likely to make more reliable policy predictions. Third, the findings from the thesis suggest that it is important for marketers to take a broader perspective when modeling consumer choice: rather than just focusing on product evaluation processes, marketers need to incorporate the setup of prior volitional stages into consumer decision-making processes. Ignoring prior volitional processes may lead to less reliable predictions on new product development and loss of insights into consumer behavioral that may help develop more innovative marketing strategies.

There are several limitations of the thesis. First, the two forms of antecedent volition (replacement strategy and goals) are studied separately. Specifically, the first essay focuses on the role of replacement strategies without examining goals; the second essay concentrates on the role of goals without investigating strategies. But it is possible that these two types of pre-evaluation volition (e.g., strategies and goals) interact with one another. Second, it is assumed that there is neither heterogeneity in antecedent volitional stages nor *taste* heterogeneity in evaluative processes conditional on the antecedent volitional stage. Third, consumers are assumed to only adopt the maximization decision rule without using other simplification decision rules. Fourth, due to the limitation of the data, the evolution of antecedent volition has not been investigated.

This thesis opens up many promising opportunities for future research. The first stream of opportunities lies in the recognition of other possible forms of prior volition that may influence consumer choice. For example, antecedent construal levels (see Trope and Liberman 2010) may influence the way product attributes are evaluated. Specifically, since it has been shown that consumers adopting top-down (bottom up) information processing mode are likely to favor desirable (feasible) options (Liu 2008), it is possible that consumers with abstract (concrete) mindset tend to value the desirability (feasibility) attributes of products, given that abstract (concrete) mindset may lead to the adoption of top-down (bottom-up) information processing mode. Integrating prior mindset formation into the understanding and modeling of consumer choice may provide greater insight into the interplay of this form of antecedent volition with evaluative processes.

Second, it might be interesting to investigate heterogeneity in prior volitional stages as well as taste heterogeneity conditional on the antecedent volition. Since the formation of prior volition stages is a higher-level decision than the evaluation of product attributes, "true" taste heterogeneity is more likely to be revealed after the heterogeneity in the pre-evaluation volition has been controlled for. Otherwise, the two types of heterogeneity are likely to be confounded with one another. Third, antecedent volition may influence the selection of decision rules. For example, prevention-focused consumers may be less likely to adopt simplification rules than promotion-focused consumers, because prevention-focused people value security/safety more than promotion-focused individuals

(Higgins 2000) and thus are less likely to ignore the presented information. Fourth, it may also be interesting to examine how antecedent volition evolves over time and how such evolution influences product evaluation, using time-series data on consumer choice.

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APPENDICES

APPENDIX 2-1 COMPUTATION OF WLLINGNESS TO PAY (WTP) FOR ATTRIBUTE CHANGES

I use two artificial products, a typical incumbent product and a typical new product, for the computation of WTP measures for the pre-specified attribute changes.

The attributes of each camera are shown in Table A.2-1. I first make the pre-specified change for an attribute of the new product, say, I change the resolution from 12.1 to 14 megapixel (see Figure 2-4). Next, I change the price of the new product by such an amount that the probability of choosing the new product remains the same as before. This price change is the Willingness To Pay (WTP) for the corresponding change in that attribute (the change of resolution from 12.1 to 14 megapixel). This procedure is repeated to compute WTP for the pre-specified change in each of the other attributes (i.e., increasing zoom from 3 to 5 times, increasing LCD size from 3.0 to 3.5 inches, adding wide-angle functionality, decreasing camera size from compact case needed to pocket size).

Table A.2-1 Cameras Used in WTP Analyses

	Incumbent Camera	New Camera
Brand	Canon	Canon
Price ($)	225	234.95
Resolution (mega pixel)	8	12.1
Zoom (times)	4	6
LCD (")	2.5	3
WideAngle	No	No
CameraSize	Compact Case Needed	Compact Case Needed

APPENDIX 3-1 EXPLORING GOAL HIERARCHIES USING DATA COLLECTED FROM SURVEY II

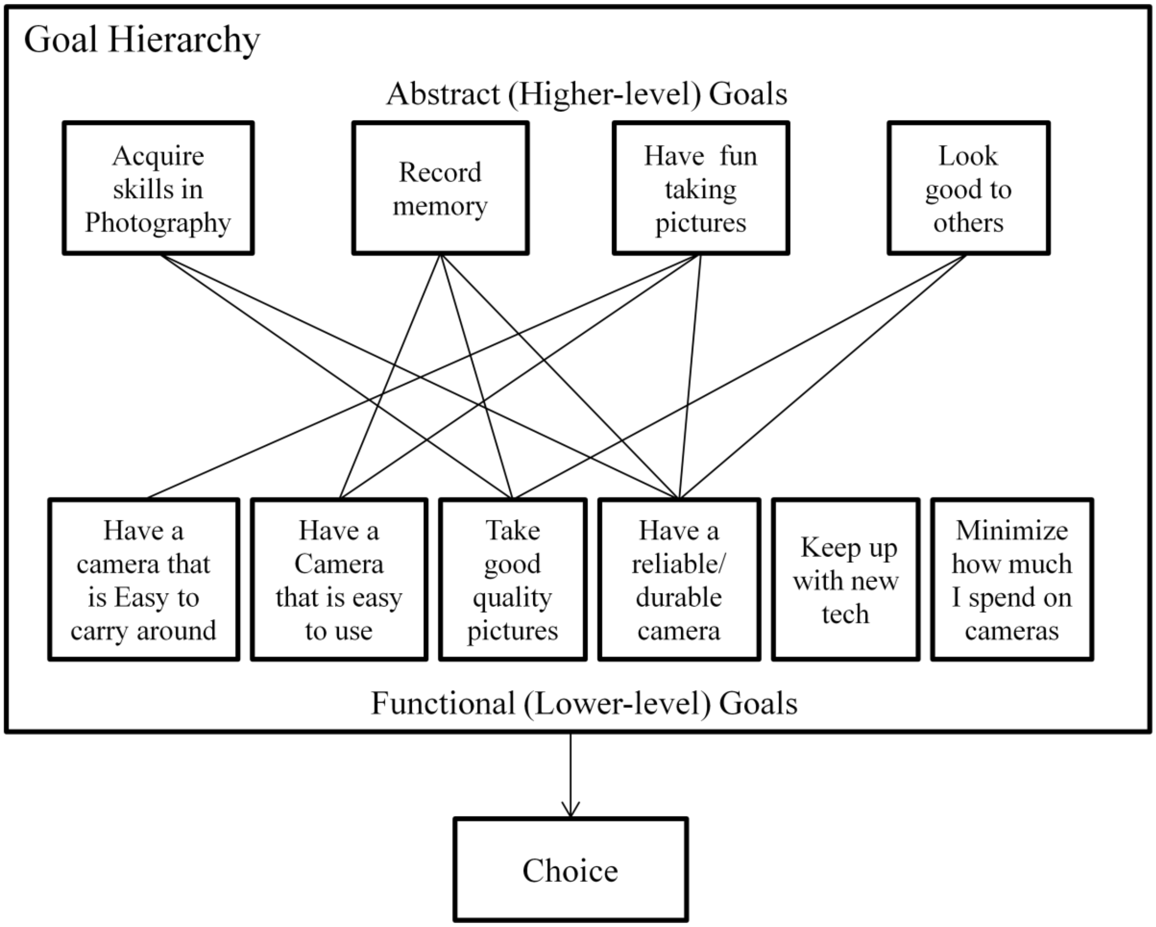
By summarizing the responses to the question on whether achieving one goal serves as means of achieving another goal (see Survey II), I report in Table A. 3-1 the percentage of respondents who stated that attaining a goal at the i^{th} row is a means of attaining a goal at the j^{th} column. For example, the number "32%" at the 1^{st} row, 2^{nd} column means that 32% percent of the sample state that attaining the goal "acquire skills in photography" is a means of attaining the goal of "record memory" . This table suggests that over 50% of respondents indicated that each abstract goal could be attained by means of a certain combination of functional goals (see the bold numbers in Table A. 3-1). This provides empirical evidence that abstract goals operate at a higher level whereas functional goals at a lower level.

Based on the percentages over 50% (in bold font) in Table A. 3-1, I graphically represent the hierarchical relationships among the self-reported goals in Figure A. 3-1. As shown in this figure, for example, the functional goals "take good quality pictures" and "have a reliable/durable camera" are means of achieving the abstract goal "acquire skills in photography". Note that the two functional goals "keep up with new technology" and "minimize how much I spend on cameras" are not considered as means of achieving any of the abstract goals listed here, nor are the two functional goals considered to be achieved by means of any abstract goals. Here I assume that these two functional goals also operate at the lower level of the goal hierarchy just as the other functional goals, as the two functional goals also provide concrete, rather than abstract, benefits to consumers. Based on Figure A. 3-1, I contend that functional goals are more likely to predict choices, because based on the Construal Level Theory (Trope and Liberman 2010) lower-level functional goals are more concrete and thus have a shorter distance toward the observed choice as compared to abstract goals. Given the presumably stronger predictive relationship between functional goals and choice and the fact that the proposed model does not explicitly incorporate goal hierarchies, I argue that the latent constructs captured by the proposed goal-based choice model are likely to be the functional goals. Therefore, I rely on self-reported functional goals for model validation.

Table A.3-1 Percentage of the Sample Reporting that the Goal at the i^{th} row is the means of achieving the goal at the j^{th} column

		Goal at the j^{th} column									
		acquire skills in photography	record memory	have fun taking pictures	look good to others	keep up with new technology	have a camera that is easy to carry	have a camera that is easy to use	take good quality pictures	minimize spending on cameras	have a reliable/durable camera
Goal at the i^{th} row	acquire skills in photography	---	32%	16%	46%	24%	15%	15%	33%	14%	16%
	record memory	22%	---	23%	35%	12%	15%	12%	7%	12%	8%
	have fun taking pictures	38%	32%	---	27%	12%	17%	13%	17%	11%	11%
	look good to others	26%	25%	21%	---	25%	18%	23%	15%	22%	8%
	keep up with new technology	28%	21%	20%	37%	---	20%	18%	24%	20%	19%
	have a camera that is easy to carry	23%	39%	**50%**	31%	23%	---	30%	17%	13%	18%
	have a camera that is easy to use	32%	**54%**	**66%**	30%	34%	20%	---	30%	19%	16%
	take good quality pictures	**56%**	**69%**	43%	**65%**	35%	15%	21%	---	18%	18%
	minimize spending on cameras	15%	18%	25%	21%	22%	12%	11%	12%	---	13%
	have a reliable/durable camera	**53%**	**67%**	**63%**	**54%**	28%	24%	27%	38%	18%	---

Figure A.3-1 Hierarchical Structure of the Self-reported Abstract and Functional Goals



APPENDIX 3-2 FORMULATING COMMUNICATION STRATEGIES FOR DIFFERENT BRANDS BASED ON THE ESTIMATION RESULTS

As discussed in the main body of this paper, marketers can improve communication with consumers by developing innovative targeting, positioning and advertising strategies on the basis of the estimation results as summarized in Table 3-9 (see the main body of the paper). Here I specifically discuss how marketers of different brands as included in the data (Canon, Panasonic, Sony and Fujifilm) can utilize the insights provided in Table 3-9 to improve their marketing communication strategies.

Canon

Canon, among the four brands in the data, is perceived to contribute most to achieving Latent Goal 1 - keep up with new technology, with respect to which a smaller camera size as well as a lower price is considered as important. Based on this insight Canon can advertise its "compact" models by emphasizing the goal of "keep up with new technology" and associating the feature of "small size" with it.

Interestingly, among the four brands Canon is also considered as contributing most to Latent Goal 4, which is as well associated with the self-reported goal "keep up with new technology." But higher zoom range, instead of smaller size, is perceived as contributing to this latent goal. This suggests that there may exist two groups of people who have different ways of evaluating the attainment of this goal: one group considers smaller camera size as the means of achieving the goal of "keeping up with the new technology" while the other group considers higher optical zoom as the means of achieving the same goal. In addition, these two groups have different price sensitivities: the former group is more price sensitive, whereas the latter group seems to use price as an indicator of high technology (note the positive price coefficient).

Different price sensitivity associated with these two latent goals (i.e., LG1 and LG4) invite the question of who wants more expensive cameras. Table 3-9 reveals that the people who have spent more money on previously purchased cameras and have higher self-reported expertise on cameras are the ones who want a more expensive camera. These findings suggest that Canon can target this high-camera-investment-and-high-expertise group with a different communication strategy than previously described. Specifically, Canon can target this group with its expensive high zoom models, emphasizing in its promotional material the association between this high zoom feature and the attainment of the goal of "keep up with new technology."

Not surprisingly, Canon, as a leading brand in both the professional and point-and-shoot cameras, is also perceived as contributing most to Latent Goal 3 (which is associated with the self-reported goal of "taking good quality pictures") among the four brands. I find that this goal can be achieved through high resolution, high zoom and water-proof functionality, and that consumers who want to achieve this goal are those who use cameras mainly for vacations and who own a SLR (see Table 3-9). Based on this insight, Canon may need to identify a third segment and target them with cameras having these features, perhaps as a backup camera for more sophisticated amateurs. The theme of such promotional material would emphasize the pursuit of the goal of "taking good quality pictures" in a vacation context by using a point-and-shoot digital camera (with high resolution, high zoom, and water proof) that is almost as good as a SLR.

Panasonic

I find that among the four brands Panasonic is perceived as contributing most to Latent Goal 2, which is associated with a combination of four self-reported goals “have a camera that is easy to carry,” “have a camera that is easy to use,” “take high quality photos” and “reliability.” Based on the multiple valued attributes with respect to this latent goal as shown in Table 3-9, it is likely that the high-speed burst shooting feature would help to achieve the two goals of “taking high quality picture” and “having a camera that is easy to use,” the smaller size of the camera to achieve the goal of “having a camera that is easy to carry”, and the water-and-shock proof feature would help satisfy the goal of “reliability.” Table 3-9 also shows that Latent Goal 2 is more likely to be pursued by consumers who use cameras mainly for vacations as well as family/friend occasions and who have bought greater number of cameras previously. Therefore, it seems that these consumers are looking for a *multi-functional* camera to achieve a *multi-faceted* goal. Based on the above understanding, Panasonic marketers can emphasize the importance of achieving this *multiple-faceted* goal and communicate how the multiple aspects of the goal can be balanced through two powerful features: high-speed burst shooting and water-proof functionality. With these features, the user who wants to capture a unique moment in a rush either in a family/friends gathering or during a vacation can be confident that his/her camera is protected.

Sony

Table 3-9 shows that Sony is perceived as contributing most to Latent Goal 5 (which is associated with the self-reported goals of “have a camera that is easy to use” and “minimize cost on cameras”) among the four brands. This latent goal seems to be achieved through low price, high zoom, small size and the water-proof feature. Consumers who are more likely to pursue this goal are those who use cameras only occasionally for family/friends gatherings, spent less money on the currently-owned P&S digital camera, and have low self-reported expertise. Based on these findings, Sony can advertise the goal of “have a reasonably-priced camera that is easy to use” and associate with it the competitive price, high zoom, smaller size and water- proof feature. But Sony marketers can also consider the possibility of re-positioning the brand in the P&S camera market by attempting to break with the existing brand associations and establishing new associations, e.g., link Sony with the goal of “having a high-tech camera that is easy to use.”

Fujifilm

The results show that Fujifilm is not associated with any of the all five latent goals (see Table 3-9). This seems to suggest that Fujifilm does not perform well in the P&S digital camera market. Under such circumstances, Fujifilm marketers can either adapt to the above-mentioned goals and become associated with them or define the brand with respect to some other goals not captured here. For example, they can define a new goal called “share life easily” and associate the brand image with this new goal by promoting the feature of "easy Facebook upload."

APPENDIX 3-3 COMPUTATION OF WLLINGNESS TO PAY (WTP) FOR ATTRIBUTE CHANGES IN THE POLICY ANALYSIS

The cameras used in the policy analysis are shown in Table A. 3-3. As described in the main body of the paper, there are two conditions for the policy analysis: the variation in attributes that are continuous variables (i.e., resolution, zoom, LCD size) is (a) within or (b) outside the range of the corresponding attributes in the data used for estimation. In each condition, I first make the pre-specified change for an attribute of Camera 2. Next, I change the price of Camera 2 by such an amount that the probability of choosing the camera with respect to Camera 1 remains the same as before. This price change is the Willingness To Pay (WTP) for the corresponding change in that attribute. This procedure is repeated to compute WTP for each of the other attributes.

Table A.3-3 Cameras Used in Policy Analyses on WTP Measures

	(a) Within-Range Variation		(b) Outside-Range Variation	
	Camera1	Camera2	Camera1	Camera2
Panasonic	no	yes	no	yes
Sony	yes	no	yes	no
Fujifilm	no	no	no	no
Price ($)	79	139	79	139
Resolution (mega-pixel)	12	12	12	16
Zoom (times)	16	8	16	16
Burst Shooting	yes	no	yes	no
Touch Screen	yes	no	yes	no
LCD Size (inches)	3.3	3	3.3	3.6
Camera Size	Pocket Size	Compact Case Needed	Pocket Size	Compact Case Needed
Water Proof	no	no	no	no
Facebook Upload	yes	no	yes	no

APPENDIX 3-4 THE SIMULATION STUDY

In the true Data Generation Process (DGP) of this simulation study, I assume that each individual has two goals (G1 and G2), and s/he evaluates product attributes with respect to each goal and *fully* adapts goal weights to choice context. Here is the general setting of the true DGP: each individual has two goals; three alternatives in each choice set and two attributes for each alternative (price and quality); each individual completes 10 choice tasks and 2000 individuals are included in each data set. Upon each data set, I estimate both the MGBCM and the LCM.

The true coefficients for the two alternative-specific constants (ASC1, ASC2), Price and Quality with respect to the first goal (G1) are 4, 2, -2, 3, whereas those with respect to the second goal (G2) are 1, 4, -6, 1 (see the column of “True Value” in Table A. 3-4). Note that these parameters represent the goal-specific attribute importance. For simplicity, I assume that the impact of individual characteristics on prior goal weighting can be summarized by a constant that represents a general tendency to prefer one goal over the other. I manipulate this general tendency across two conditions: (a) the two goals are equally preferred as a prior, the constant being 0; (b) the second goal (G2) is preferred over the first goal (G1) as a prior, the constant being 3. 100 data sets are generated for each condition.

I find that (see Table A. 3-4), in each condition, the MGBCM can correctly identify the true number of goals, (i.e., two) but the LCM cannot. Specifically, the LCM model can only identify one latent class regardless of conditions, as the BICs of the two-class model are always greater than those of the one-class model (i.e., the BIC of the two-class vs. one-class model is 21408 vs. 21359 for condition a and 24397 vs. 24354 for condition b).

I also find that, across the two conditions, the MGBCM can successfully recover the true parameters for goal-specific attribute importance but the LCM cannot. Note that in Table A. 3-4 the numbers besides (within) the parentheses are the average parameter estimates (standard errors) over the 100 simulated data sets. I compare each parameter estimate (PE) with the corresponding true value (TV) and test the null hypothesis PE=TV, i.e., PE is not significantly different from TV. If the null hypothesis is rejected at α=0.05, then the parameter is biased and marked with "*". The results show that none of the parameters estimated by the MGBCM is biased; but all the parameters estimated by the LCM are biased (i.e., marked with "*")[5] except for the coefficient for "ASC1_G1" under condition (a).

To summarize, this simulation study shows that, when individuals fully adapt their prior goal weights to the choice context, the utility-based LCM that does not account for goal weight adaptation fails to capture goals and thus produces biased parameters for goal-specific attribute importance.

[5] As only one set of attribute parameters has been estimated for the LCM due to the identification of a single latent class, I compare this set of attribute parameters with (a) the true parameters for attribute importance with respect to G1 and with (b) the true parameters for attribute importance with respect to G2, respectively. I report the results based on comparison (a) as the t-stats for this comparison are relatively smaller. Such comparison serves as a more conservative test of the hypotheses.

Table A. 3-4 Parameter Estimates of the Multiple-Goal-Based Choice Model (the MGBCM) and the Latent Class Model (the LCM) in the Simulation Study

	Condition (a): G1 and G2 are Equally Attractive as a Prior				Condition (b): G1 is more Attractive than G2 as a Prior			
	True Value	The MGBCM	The LCM		True Value	The MGBCM	The LCM	
Goal-specific Attribute Evaluation								
ASC1_G1	4	3.999(0.071)	3.909(0.048)		4	4.013(0.132)	3.093(0.043)	*
ASC2_G1	2	1.996(0.086)	2.423(0.046)	*	2	1.997(0.194)	3.218(0.044)	*
Price_G1	-2	-2.004(0.099)	-2.543(0.05)	*	-2	-2.034(0.112)	-3.622(0.052)	*
Quality_G1	3	2.991(0.075)	2.585(0.05)	*	3	2.972(0.085)	1.896(0.044)	*
ASC1_G2	1	1.002(4.237)			1	0.854(0.357)		
ASC2_G2	4	3.999(0.5)			4	4.016(0.087)		
Price_G2	-6	-5.969(0.455)			-6	-6.024(0.146)		
Quality_G2	1	0.977(0.22)			1	0.999(0.09)		
Prior Goal Weighting								
General Tedency of Prefering G2 over G1	0	0.004(0.581)			3	2.958(0.227)		
Goodness-of-Fit								
k		9	4			9	4	
LL		-10491	-10659			-11309	-12157	
BIC		21072	21359			22707	24354	

Note: 1. Besides the parentheses is the mean of the estimated parameters; inside the parentheses is the mean of the estimated standard errors.

2. BIC refers to Bayesian Information Criterion.