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Consideration-Set Heuristics

Abstract

Consumers often choose products by first forming a consideration set and then choosing from among considered products. When there are many products to screen (or many features to evaluate), it is rational for consumers to use consider-then-choose decision processes and to do so with heuristic decision rules. Managerial decisions (product development, marketing communications, etc.) depend upon the ability to identify and react to consumers' heuristic consideration-set rules. We provide managerial examples and review the state-of-the-art in the theory and measurement of consumers' heuristic consideration-set rules. Advances in greedoid methods, Bayesian inference, machine-learning, incentive alignment, measurement formats, and unstructured direct elicitation make it feasible and cost-effective to understand, quantify, and simulate "what-if" scenarios for a variety of heuristics. These methods now apply to a broad set of managerial problems including applications in complex product categories with large numbers of product features and feature-levels.

1. Introduction

Consumers often face a myriad of alternative products, whether it is deodorants (more than 30 brands on the market) or automobiles (more than 350+ model-make combinations). Evidence suggests that consumers, who are faced with many products from which to choose, simplify their decisions with a consider-then-choose decision process in which they first identify a set of products, the consideration set, for further evaluation and then choose from the consideration set. There is also compelling evidence that consumers use heuristic decision rules to select the products for their consideration sets. Both the consider-then-choose decision process and the heuristic decision rules enable consumers to screen many products more rapidly with reduced cognitive and search costs and are thus both fast and frugal heuristics as discussed in Gigerenzer and Goldstein (1996), Gigerenzer and Selten (2001), Goldstein and Gigerenzer (1999, 2002), and elsewhere in this issue. In this paper we review recent developments in the measurement of heuristics for consideration-set decisions and the managerial implications of such heuristics.

We begin with examples where consideration sets are key to business strategy. We then turn to the science and review arguments that it is typical, and rational, for consumers to simplify multi-product decisions with a consider-then-choose decision process and it is typical, and rational, for consumers to use decision heuristics to form consideration sets. With this motivation, we review the heuristics that have been identified and show that most can be represented by disjunctions of conjunctions. The heart of the paper reviews recent advances in the identification and measurement of decision heuristics and includes illustrations of how the knowledge of such heuristics affects managerial strategies.

2. Managerial Relevance

In 2009 two American automakers declared bankruptcy. These two automakers were once part of the "Big 3" and enjoyed a dominant position in the American market. However, through the 1980s and the 1990s consumers turned to a variety of Japanese and European manufacturers who provided vehicles that consumers perceived as more reliable, better engineered, or that met their needs more effectively. A US automotive manufacturer (disguised here as USAM) was faced with a situation around 2004-2005 where roughly half of US consumers (and 64% in California) would not even consider a USAM vehicle (Hauser, Toubia, Evgeniou, Dzyabura, and Befurt 2010).

In response, USAM invested heavily in quality, reliability, styling, and interior design to produce vehicles that would be rated well. By 2007 a USAM car was tied with Lexus as the most dependable vehicle (J. D. Power) and by 2008 a USAM car was the top-rated US vehicle in *Consumer Reports*. But these achievements were not enough to entice consumers to consider USAM vehicles in sufficient numbers.

Part of the problem (though not the only cause of the bankruptcy) was that consumers never experienced the improved products because they never considered them. USAM had evidence that if consumers could be persuaded to test drive a USAM car, then they would again trust USAM, consider USAM, and purchase USAM vehicles. For example, in one experiment USAM brought consumers to a test track where they could test drive up to 100 vehicles from Acura, BMW, Buick, Cadillac, Chevrolet, Chrysler, Dodge, Ford, Honda, Lexus, Lincoln, Mercedes, Pontiac, Saab, Saturn, Toyota, Volkswagen, and Volvo without sales pressure. In another experiment USAM provided competitive brochures on its website in the hopes that such a one-

stop, unbiased source would encourage consumers to consider USAM vehicles. Indeed, in an elaborate multi-year experiment, trust, consideration, and purchase of USAM vehicles increased when this competitive information broke down barriers to USAM consideration (Liberali, Urban and Hauser 2013). These multi-million dollar programs were successful because they changed the heuristics that consumers used to select vehicles to consider. Without mechanisms to lower consideration costs or raise expected benefits, consumers eliminated USAM brands without detailed evaluation.

Another example is Suruga Bank. Suruga is a commercial bank in the greater Tokyo area that has a significant online presence through virtual banking. However, Suruga was a relatively small player in the Japanese card-loan market. A card loan is a loan of ¥3-5 million in which the consumer is given a bank card and a PIN and pays interest only on the amount withdrawn. In 2008 Japanese consumers had approximately ¥25 trillion available in card-loan balances. While card-loan products vary on interest rates, credit limits, credit screening, and customer service, consumers are more likely to choose a product from well-known banks – likely an example of the fast-and-frugal recognition heuristic for consideration (Gigerenzer and Goldstein 1996; Goldstein and Gigerenzer 1999; 2002). [For empirical tests of the recognition heuristics see Bröder and Eichler (2006), Coates, Butler and Berry (2004, 2006), Frosch, Beaman, and McCloy (2007), and Marewski, Gaissmaier, Schooler, Goldstein, and Gigerenzer (2010).] In response, Suruga developed a customer-advocacy website that morphed to match customers' cognitive and cultural styles while providing unbiased information on competitive banks. In a field experiment, the website led to substantial increases in trust and consideration of Suruga Bank (Hauser, Urban and Liberali 2013).

The GM and Suruga strategies were evaluated with careful field experiments (a rarity in

business practice), but there are many anecdotes to the importance of consideration sets. In the US, consideration-set sizes for most consumer package goods categories are approximately $1/10^{th}$ of the number of brands that are available to consumers in the product category. For example, Hauser and Wernerfelt (1990) report the following average consideration set sizes: deodorants (3 brands), shampoos (4 brands), air fresheners (2.2 brands), laundry detergents (4 brands), and coffees (4 brands). (The usual explanation is the benefit vs. cost tradeoff discussed in §3, but cognitive limitations might also influence costs. See Lynch and Srull 1982, Nedungadi 1990, Paulssen and Bagozzi 2005, Punj and Brookes 2001, and Simon 1967.) It is not surprising that typical advertising and communications budgets can be in the tens (or even hundreds) of million dollars for a new consumer package good. Advertising drives consideration. (See, for example, Coates, Butler and Berry 2004; 2006.) If a brand is in the consideration set, all else equal, the firm has reduced the odds of a sale from, say, 1-in-40 to 1-in-4. For example, in deodorants Hauser (1978) showed that 80% of the uncertainty in predicting consumer choice is resolved by simply knowing each consumer's consideration set. This fact is used by pretest market forecasting methods which rely upon consideration-set measurement to increase their forecasting accuracy (Ozer 1999; Urban and Hauser 1993).

Advertising gains recognition and to the extent that consumers use a recognition heuristic to form their consideration sets (e.g., Marewski, Gaissmaier and Gigerenzer 2010), the recognition heuristic is key to managerial strategy. Other decision heuristics matter as well. The recent introduction of many "natural" or "organic" products represents a reaction to decision heuristics in which consumers eliminate brands that do not have these aspects. (Following Tversky 1972, we use "aspect" to mean a level of a product feature.)

We return to managerial issues in a §7, but first review theories that suggest that both

consideration sets and decision heuristics are rational for consumers.

3. Consideration Sets are Rational

In seminal observational research Payne (1976) identified that consumers use consider-then-choose decision processes. This phenomenon is firmly rooted in both the experimental and prescriptive marketing literature (e.g., Bronnenberg and Vanhonacker 1996; Brown and Wildt 1992; DeSarbo, Lehmann, Carpenter, and Sinha 1996; Hauser and Wernerfelt 1990; Jedidi, Kohli and DeSarbo, 1996; Mehta, Rajiv, and Srinivasan, 2003; Montgomery and Svenson 1976; Roberts and Lattin, 1991; Paulssen and Bagozzi 2005; Shocker, Ben-Akiva, Boccara, and Nedungadi 1991; Wu and Rangaswamy 2003). While there are many potential explanations for the consideration-set phenomenon, the most-common explanation is based on arguments that it is rational for consumers to form consideration sets. Like many decision heuristics, consideration sets are consistent with a benefit-vs.-cost tradeoff.

Suppose that the utility that a consumer derives from choosing product j is $\tilde{u}_j$. Prior to detailed evaluation this utility is a random variable. If the evaluation was perfect and the consumer considered n products, the consumer would choose the maximum utility from the set of n products. Thus, prior to evaluation, the expected utility is the expected value of the maximum of the n random variables, $E[\max\{\tilde{u}_1, \tilde{u}_2, \dots, \tilde{u}_n\}]$. We expect this maximum value to be a concave function of n as shown in Figure 1. For example, if each $\tilde{u}_j$ is an independently normally distributed random variable with mean, μ, and variance, σ^2, then this expected maximum value is given by $\mu + \sigma e_n$ where e_n is a concave tabled function for $n \geq 1$ (Gumbel 1958, 131; Stigler 1961, 215). Even if the consumer cannot choose the best of the set with certainty, the expected maximum value is just $\mu + \rho R \sigma e_n$ where ρ and R are the validity and reliability of the consumer's

ability to choose the maximum utility from a set (Gross 1972). These formulae describe situations when the consumer chooses the n products randomly from the set of available products. If the consideration-set decision heuristic is even moderately effective the consumer will select such that better products are more likely to be included in the consideration set. Even a moderately-effective heuristic reinforces the concavity in n of the expected utility of choosing from a consideration set.

[Insert Figure 1 about here.]

Costs of evaluating more completely the considered products are likely to be convex (Figure 1) – although the benefit-vs.-cost arguments also apply if costs are linear in n. We expect convexity because more comparisons likely mean more features and more products must be compared to select the best of n products. (Recall that the decision within the consideration set is likely a more exhaustive evaluation than the heuristic screening used to decide which products are in the consideration set.)

When the benefit curve is concave and the cost curve is convex then either they diverge from the beginning and the consumer considers no products or they cross and there is a point at which the evaluation costs exceed the benefit from the chosen product. The optimal size of the consideration set is the n that maximizes the difference between the benefits and costs. The optimal consideration-set size is shown as n^* in Figure 1. While there is no guarantee that n^* is less than the total number of products available, the empirical evidence is strong that in most product categories consumers do not consider all products on the market.

4. Consideration-Set Heuristics are Rational

Experimental studies have long demonstrated that decision heuristics are common and

represent reasonable benefit-vs.-cost tradeoffs (e.g., Bettman, Luce and Payne 1998; Brand-staetter, Gigerenzer and Hertwig 2006; Dawkins 1998; Einhorn and Hogarth 1981; Gigerenzer and Goldstein 1996; Gigerenzer, Hoffrage and Kleinbolting 1991; Gigerenzer and Selten 2001; Gigerenzer and Todd 1999; Hogarth and Karelaia 2005; Hutchinson and Gigerenzer 2005; Johnson and Payne 1985; Lichtenstein and Slovic 2006; Martignon and Hoffrage 2002; Payne, Bettman, and Johnson 1988, 1993; Simon 1967; Shugan 1980). An example heuristic decision rule might be a conjunctive rule in which the consumer considers automobiles with the aspects of "sporty coupe," "sunroof," and "moderate fuel economy." Another heuristic decision rule might be a lexicographic rule in which the consumer ranks aspects and considers the n^* products that rank highest on the first aspect, then the second aspect, and so on until n^* products are considered. Special cases of lexicographic decision rules include "take the best," in which aspects are ranked on their ability to discriminate consider from not consider, and "recognition," in which the consumer considers only those automobiles that he or she recognizes.

In the realm of decisions about factual alternatives such as "which city is larger," heuristic decision rules are often robust and provide predictions that are more accurate than more-exhaustive evaluations (Brighton 2006; Gigerenzer and Brighton 2007, 2009; Marewski, Gaissmaier, and Gigerenzer 2010). In other cases, heuristics do almost as well (e.g., Bröder and Gaissmaier 2007). There are many potential explanations for the predictive success of simple heuristics including (1) heuristics make efficient use of data in environments to which the heuristic is adapted, (2) heuristics are robust to missing data, (3) heuristics provide optimal solutions to indexable dynamic programs (Gittins 1979), and (4) heuristics provide "complexity control" to avoid overfitting based on "training" experiences (Vapnik 1998). For consideration decisions we do not know which "answer" is best. Indeed the decision maker, the consumer, is the final arbiter

of "correct." Nonetheless, we expect that simple heuristics will do almost as well as complete evaluations or, in some cases better.

Recent research in marketing compares the predictive ability of decision heuristics to more-complex additive decision models. For most consumers, simple decision heuristics predict consideration sets as well or better than additive "conjoint-analysis" models and often better than models that are constrained to be truly compensatory (Bröder 2000; Dieckmann, Dippold and Dietrich 2009; Ding, Hauser, Dong, Dzyabura, Yang, Su, and Gaskin 2011; Gilbride and Allenby 2004; Jedidi and Kohli 2005; Kohli and Jedidi 2007; Marewski, Gaissmaier and Gigerenzer 2010; Yee, Dahan, Hauser, and Orlin 2007). Expanding the arguments of §3, we argue that decision heuristics, when used, are rational for consideration-set decisions.

In Figure 2 we repeat the benefit and cost curves for comprehensive evaluation within the consideration set. The horizontal axis is again the number of products evaluated and the optimal full-evaluation consideration-set size (n^*) is shown for comparison with Figure 1. The lighter lines to the left of Figure 2 are the same as in Figure 1. Now suppose a consumer uses a decision heuristic to select products for his or her consideration set. Even if the decision heuristic compromises his or her ability to select the highest utility product from the consideration set, empirical evidence suggest that this compromise is slight. This is shown as the heavier benefit line to the right in Figure 2.

[Insert Figure 2 about here.]

On the other hand, decision heuristics, such as the recognition heuristic or simple conjunctive heuristics (screen on a few "must have" features) clearly cost less to implement. These costs can be cognitive, but they might also include explicit search costs. For example, to evaluate

fully an automobile make-model, consumers search the Internet, talk to friends, and read reviews. Visiting dealers for test drives is even more costly. The heuristic costs are shown as a heavier line to the left in Figure 2. They are lower, in part, because the consumer evaluates fewer features with an heuristic and thus spends less time, money, and cognitive effort obtaining information on those features. We have shown the benefits from selecting from n products heuristically as slightly lower than full evaluation. Our arguments are even stronger if the heuristics are, in fact, better at identifying the best product from the consideration set.

Repeating the arguments of the previous section we see an illustrative case where the net benefit obtained using the heuristic (heavy dotted line) is greater than the net benefit of comprehensive evaluation. The consumer is better off using an heuristic within the consideration set.

Fortunately, the arguments in Figure 2 apply recursively to the consideration-set decision. We replace the horizontal axis with the number of products screened (n_s) and change the benefit decision to the benefit from screening n_s products for consideration. Because the decision within the consideration set maximizes the benefit-to-cost difference, the consideration-set decision need only succeed at including a high-benefit product as one of n products in the consideration set when screening n_s products.

Naturally, the comparison between a comprehensive evaluation and an heuristic evaluation will depend upon the specific parameters of the product category. For example, if there are relatively few products and each product is particularly easy to evaluate, the cognitive and search costs for exhaustive evaluation will be small and the consumer might evaluate all products. On the other hand, if the number of products is large and each product is difficult to evaluate exhaustively, then it is likely that a decision heuristic will provide the best benefit-to-cost tradeoff.

Figure 2 illustrates situations where it is reasonable that the benefits and costs are such that a decision heuristic is best for consumers. This is consistent with the empirical evidence: decision heuristics are common in all but very simple product categories (Payne, Bettman and Johnson 1988; 1993). We now describe common decision heuristics.

5. Common Consideration-Set Decision Heuristics

Many heuristic decision rules have been studied in the marketing literature (e.g., Bettman and Park 1980a, 1980b; Chu and Spires 2003; Einhorn 1970, 1971; Fader and McAlister 1990; Fishburn 1974; Frederick (2002), Ganzach and Czaczkes 1995; Gilbride and Allenby 2004, 2006; Hauser 1986; Hauser et al. 2010; Jedidi and Kohli 2005; Jedidi, Kohli and DeSarbo 1996; Johnson, Meyer and Ghose 1989; Leven and Levine 1996; Lohse and Johnson 1996; Lussier and Olshavsky 1997; Mela and Lehmann 1995; Moe 2006; Montgomery and Svenson 1976; Nakamura 2002; Payne 1976; Payne, Bettman, and Johnson 1988; Punj and Brookes 2001; Shao 1993; Svenson 1979; Swait 2001; Tversky 1969, 1972; Tversky and Sattath 1979; Tversky and Simonson 1993; Vroomen, Franses and van Nierop 2004; Wright and Barbour 1977; Wu and Rangaswamy 2003; Yee et al. 2007). We describe the heuristics that appear to be the most common and are the most likely to affect managerial decisions in product development, advertising, and other communications strategies. We describe these heuristics using the terms common in the marketing literature pointing out where these heuristics are similar to those described in the "adaptive toolbox" literature (Gigerenzer, Todd, and the ABC Research Group 1999). (By adaptive toolbox we refer to the assumption that consumers use a repertoire of heuristic decision rules that are adapted to the decision-making environment.) The heuristics common in the marketing literature are conjunctive, disjunctive, subset conjunctive, lexicographic, elimination-by-aspects, and disjunctions of conjunctions.

Managerially-Relevant Heuristic Decision Rules

Table 1 summarizes the example decision rules that are discussed in this section.

[Insert Table 1 about here.]

Conjunctive. A consumer using a conjunctive rule screens products with a set of "must have" or "must not have" rules. For example, Hauser, et. al. (2010a) describe "Maria" whose consideration set consists of a "sporty coupe with a sunroof, not black, white or silver, stylish, well-handling, moderate fuel economy, and moderately priced." In a conjunctive rule, if all of the must-have and all of the must-not-have rules are satisfied, Maria will consider the vehicle. In the formal definition of a conjunctive rule all features have minimum levels, but the minimum levels can be set so low as to not eliminate any products. These non-critical aspects are often not mentioned in the rule.

Disjunctive. A consumer using a disjunctive rule accepts products if they satisfy at least one "excitement" rule. If a consumer says she will consider any hybrid sedan, then she is applying a disjunctive rule. Another example is a consumer who will consider any crossover vehicle. The rule is also disjunctive if the consumer will consider all hybrids and all crossovers.

Subset conjunctive. Some screening rules allow greater initial variation than either conjunctive or disjunctive rules. In a subset conjunctive rule, consumers consider any product that satisfies S must-have or must-not-have rules. For example, Maria stated nine conjunctive constraints but she might be willing to consider a car that satisfies seven of the nine. An Audi A5 does not have a sunroof and is not moderately priced, but Maria might be willing to consider it. Formally, the subset conjunctive model implies consideration if any set of S features satisfy the conjunctive rules.

Lexicographic. A consumer using a lexicographic rule first ranks the aspects. For example, Maria might rank the aspects as sporty coupe, sunroof, not black, white or silver, stylish, well-handling, moderate fuel economy, and then moderately priced. She ranks first all sporty coupes, then among the sporty coupes all those that have a sunroof, and then among all sporty coupes with sunroofs those that are not black, white, or silver, and so on until all cars are ranked. Any car that is not a sporty coupe is ranked after sporty coupes but, within non-sporty-non-coupes she uses the other lexicographic aspects to rank the cars. As defined, lexicographic rules rank all products, but we are only interested in the consideration decision. That is, we are focusing on decision rules that distinguish between considered and not-considered products. To make a consideration decision, the consumer must decide on a consideration-set-size cutoff, n^*, using arguments such as those in Figures 1 and 2.

However, given a consideration-set-size cutoff, a lexicographic rule is strategically equivalent to, and hence empirically indistinguishable from, a conjunctive rule. For example, if Maria's uses the nine aspects conjunctively to form a consideration set, she will get the same consideration set that should/would have gotten had she used the same nine aspects in any lexicographic order. In general, for a given consideration set, if there is a lexicographic rule consistent with the consideration set then there is also a conjunctive rule consistent with the consideration set, and vice versa. Different data, say ranking within the consideration set or observations of the order in which products are added to a consideration set, might distinguish a lexicographic rule from a conjunctive rule. See, for example, Yee, et. al (2007). However, when we observe consider vs. not consider, the high-ranked distinguishing aspects become equivalent to must-have aspects.

Elimination by aspects (EBA). A consumer using an (deterministic) EBA rule selects an

aspect and eliminates all products that do not have that aspect. The consumer continues selecting aspects and eliminating products until the consideration set is formed. For example, Maria might first eliminate all non-sporty-coupes, then sporty coupes that do not have a sunroof, then black, white, and silver sporty coupes with sunroofs, etc. Tversky (1972) proposed EBA as a probabilistic rule where consumers select aspects proportional to their measures, but most applications use a deterministic EBA with aspects in a fixed order (Hogarth and Karelaia 2005; Johnson, Meyer and Ghose 1989; Montgomery and Svenson 1976; Payne, Bettman, and Johnson 1988; and Thorngate 1980). EBA is primarily a choice rule; for consideration sets, deterministic EBA degenerates to a conjunctive consideration heuristic for the same reasons that lexicographic degenerates to a conjunctive consideration heuristic.

Disjunctions of conjunctions (DOC). A DOC rule generalizes subset conjunctive rules to allow any combination of conjunctions. For example, Maria might consider any sporty coupe that has a sunroof and handles well <u>and</u> she might consider any sporty coupe with moderate fuel economy. (Notice that the first conjunction has three aspects and the second conjunction has two aspects; the conjunctions need not have exactly S aspects.) It is easy to show that a DOC rule generalizes conjunctive rules (a DOC rule with just one conjunction), disjunctive rules (a DOC rule with each conjunction having one aspect), and subset conjunctive rules. As argued above DOC rules also generalize lexicographic and EBA rules when they are equivalent to conjunctive rules.

Compensatory. Compensatory rules are usually classified as comprehensive evaluation rules rather than heuristics, but we include them here for completeness. In a compensatory rule some aspects (sporty coupe) can compensate for the lack of other aspects (moderate price). Typically, a compensatory rule is an additive rule in which the consumer assigns "partworths" to eve-

ry aspect and acts as if he or she sums the partworths to obtain an overall utility for the product. (Formally, the utility model can include interactions, but interactions are not commonly modeled.) To be considered truly compensatory, the (additive) partworth ratios must be such that good aspects can actually compensate for bad aspects (formal conditions given later in this section). In a compensatory rule a consumer considers every product above a threshold in utility.

A special case of a compensatory rule is an equal-weights rule in which the values of features as simply added (Dawes 1979; Einhorn and Hogarth 1975). If the utility of a feature is already scaled appropriately an equal-weights rule is equivalent to a compensatory rule (e.g., utility of lower price plus utility of ride-and-handling plus utility of body style). If values of features are continuous (mile-per-gallon, top speed, leg room) or if the features are binary (sunroof or not, sporty coupe or not) an equal-weights rule is an heuristic relative to an unequal weighting.

Relationship to Adaptive Toolbox Heuristics

The adaptive toolbox hypothesis and fast and frugal decision rules apply to decisions and judgments in general. For example, prototypical examples include judging the size of German cities or deciding which candidate for whom to vote (Gigerenzer and Goldstein 1996, Marewski, Gaissmaier and Gigerenzer 2010). We expect a relationship between the adaptive toolbox heuristics and consideration-set heuristics. (After all, consideration-set decisions are still decisions.)

For example, the recognition heuristic is a disjunctive rule in which the consumer considers those products which he or she recognizes (Goldstein and Gigerenzer 1999; 2002). There are many parallels between adaptive-toolbox heuristics and consumer-decision heuristics. Early applications of simulated stores for forecasting new product sales used aided or unaided awareness to estimate consideration (Silk and Urban 1978, Equations 22-23). Gilbride and Allenby (2004,

401) report that "consumers screen alternatives using attributes that are well known, as opposed to the new and novel." Many marketing actions attempt to make consumers familiar with a brand in the hopes that consumers will choose familiar brands – sufficient exposure to a brand name is often sufficient to enhance positive attitudes toward the brand (Zajonc 1968; Janiszewski 1993).

The take-the-best (TTB) heuristic ranks cues by their validities in discriminating among alternatives (Gigerenzer and Goldstein 1996). As Martignon (2001) argues, TTB is a lexico-graphic rule and, hence, for consideration sets, TTB is a DOC rule. The "minimalist" algorithm is a form of EBA with equal aspect measures and, hence, in a more-deterministic form is also a DOC rule. When features are binary and the consumer simply counts the positive features, an equal-weights rule is known as a tallying rule (Gigerenzer and Goldstein 1996; Marewski, Gaissmaier and Gigerenzer 2010). There are many other parallels between heuristic rules to evaluate products and heuristic decision rules in the adaptive-toolbox literature. Both domains suggest that heuristics are adaptive, for example, consumers often choose different considera-tion-set heuristics depending upon context (e.g., Payne, Bettman, and Johnson 1993).

Cognitive Simplicity and Ecological Regularity

Chase, Hertwig and Gigerenzer (1998) argue further that simple rules have evolved be-cause they work well in environments in which consumers make decisions. Such rules "capital-ize on environmental regularities to make smart inferences (p. 209)." For example, if sporty cars tend to be fast and handle well, the consumer might use sporty as a surrogate for fast and handle well. If the consumer is unsure of his/her preferences and cannot fully form those preferences without extensive driving experience, the consumer might make a better consideration decision by evaluating the vehicle on those features about which he/she is most sure. For example, if the

consumer likes sporty styling and all consumers who like sporty styling also like speed and good handling, the consumer might assume it is rational for the manufacturers to bundle speed and good handling with sporty styling. In this case the consumer would consider sporty cars comforted in the knowledge that (1) they are likely speedy and handle well and (2) after consideration he/she can assess those features before committing to a final purchase.

Cognitive simplicity and ecological regularity help identify consumers' decision heuristics. For example, DOC rules generalize all proposed heuristics, but they are, in a sense, too general. If we seek to infer a DOC rule based on an observed consideration set, many DOC rules are consistent with the observed consideration. (One such DOC rule is the trivial rule in which each of n conjunctions matches one of the n considered products.) To estimate DOC rules and to make DOC rules consistent with the research cited in §3 and §4, researchers impose cognitive simplicity. For example, Hauser, et al. (2010) constrain each conjunction to have no more than S aspects or no more than P conjunctions. These simpler DOC (S, P) rules capture the spirit of a fast-and-frugal hypothesis because the constraints balance benefit with cognitive (or search) costs. By extension, when we try to identify heuristics to explain observed consideration sets, we should give more weight to heuristics that are common among consumers. For example, algorithms to identify DOC heuristics break ties using data from observations about other consumers' consideration sets.

Curse of Dimensionality in Aspects

In subsequent sections we review recent advances in the ability of researchers to identify decision heuristics from *in vivo* consideration-set decisions. It is a paradox that the identification of a decision heuristic from observed data is substantially more difficult than established meth-

ods to identify additive decision rules. That is, specific simpler rules are harder to identify than specific more-complex rules. The challenge arises because decision heuristics are defined on a discrete space of potential rules. Because additive rules are defined on a continuous space the best-fit optimization problem requires only that we identify the value of M (or fewer) partworths where M is the number of aspects. Realistic problems can have as many as $M = 53$ aspects as in the Ding, et al. (2011) automotive application. While such large M's present a measurement challenge, advanced hierarchical Bayes methods make it feasible to infer the M or fewer parameters per consumer that are needed for additive rules.

On the other hand, the search for the best-fit heuristic requires that we solve a combinatorial optimization problem. For example, with M aspects there are $M!$ lexicographic rules – for $M = 53$, $M!$ is on the order of 10^{69} potential rules. To choose the best-fitting, most-general DOC model, the search is "easier," but we would still have to search over all feasible combinations of $2^{53} \cong 10^{16}$ conjunctions (about 9 quadrillion rules). Fortunately, when we impose cognitive simplicity we reduce greatly the number of potential decision rules making the combinatorial search feasible. Cognitive simplicity becomes a form of complexity control, a method in machine learning that imposes constraints to prevent best-fit optimizations from exploiting unobserved random error (Cucker and Smale 2002; Evgeniou, Boussios and Zacharia 2005; Hastie, Tibshirani and Friedman 2003; Langley 1996; Vapnik 1998). Ecological regularity further restricts our search for decision rules. It is not unlike shrinkage to population means as used in hierarchical models in Bayesian additive-utility models (e.g., Lenk, DeSarbo, Green, and Young 1996; Rossi and Allenby 2003).

Additive and Compensatory are not Equivalent

A final challenge in identifying decision heuristics from observed consideration-set decisions is the generality of the additive model. As Bröder (2000), Jedidi and Kohli (2005), Kohli and Jedidi (2007), Olshavsky and Acito (1980), and Yee, et al. (2007) illustrate, an additive model can represent many decision heuristics. For example, with M aspects, if the partworths have the values, $2^{M-1}, 2^{M-2}, \ldots, 2, 1$, then the additive model is strategically equivalent to a lexicographic model. Similarly, if S partworths have a value of β and the remaining partworths a value of 0, and if the utility cutoff is $S\beta$, then the additive model is strategically equivalent to a conjunctive model.

Bröder (2000) exploits this strategic equivalency by classifying respondents as either lexicographic or compensatory depending upon the estimated values of the partworths. (This method works well when M is small, but is extremely sensitive to measurement error when M is large as in the automotive example which requires ratios of 10^{16} to 1 in the additive model.) To address this indeterminacy, Yee, et al. (2007) generalize Bröder's analysis by defining a q-compensatory model in which no importance value is more than q times as large as any other importance value. (An importance value is the difference between the largest and smallest partworth for a feature.) When this constraint is imposed on the additive benchmark, we can compare the predictive ability of an heuristic to a compensatory model. Without such a constraint, an additive rule can be either compensatory or non-compensatory.

6. Recent Developments in Identifying Consideration-Set Heuristics

Marketing scientists have reacted to the managerial importance of consideration-set heuristics by developing models and measurement methods to identify which heuristics consumers

use to screen products for consideration sets. These approaches fall into three basic categories:

- consideration-set heuristics as latent; identify consider-then-choose processes by observing final choice

- consideration-set decisions observed; identify heuristics as those that best describe observed consideration-set decisions

- ask consumers to describe their heuristics (with incentives to do so accurately).

We review each in turn while reporting empirical comparisons and predictive success. In §7 we return to managerial applications.

Consideration-Set Heuristics as Latent

When the number of aspects is small-to-moderate and the decision rules are assumed to be relatively simple (e.g., conjunctive), the number of parameters that must be estimated to identify consideration-set heuristics is moderate. In these cases, researchers can model consideration as a latent, unobserved, intermediate stage in the consider-then-choose decision and estimate the parameters that best describe observed choices. For example, Gilbride and Allenby (2004) assume either conjunctive, disjunctive, or linear screening rules for the consideration stage and additive decision rules for choice from the consideration set. They derive the data likelihood for their model and infer the best description of the latent rules with Bayesian methods. With their streamlined model they find that 92% of their respondents are likely to have used a conjunctive or disjunctive screening rule for consideration-set decisions. See also Gensch (1987), Gensch and Soofi (1995a, 1995b), Gilbride and Allenby (2006), and van Nierop, Bronnenberg, Paap, Wedel, and Franses (2010).

Choice-set explosion is another common latent method when the number of products, N,

is small. In choice-set explosion, researchers assume that each of the 2^N choice sets is possible with probabilities given by the screening rules. For example, some methods assign a probability to each aspect to represent the likelihood that it is used in a conjunctive rule. These aspect probabilities imply data likelihoods for each choice set. Researchers assume further that consumers choose within the consideration set based on an additive model. Together these assumptions imply a data likelihood from which both the conjunctive probabilities (consideration decision) and the partworths (decision within the consideration set) are inferred. See Andrews and Srinivasan (1995), Chiang, Chib and Narasimhan (1999), Erdem and Swait (2004), Punj and Staelin 1983, and Swait and Ben-Akiva (1987). Choice-set explosion works best in product categories where there are a few dominant brands, but quickly becomes infeasible as N increases. Some hybrid methods relax this choice-set curse of dimensionality with independence assumptions or by asking consumers to state the consideration-set probabilities (van Nierop, et al. 2010; Swait 2001).

Infer Heuristics from Observed Consideration Sets

For over forty years researchers have asked consumers to report their consideration sets. Measures exhibit high reliability and validity and forecast well (Brown and Wildt 1992; Hauser 1978; Silk and Urban 1978; Urban and Katz 1983). With the advent of web-based interviewing, new formats have been developed and tested (Ding, et al. 2011; Gaskin, Evgeniou, Bailiff, and Hauser 2007; Hauser, et al. 2010;Yee, et al. 2007.) The "bullpen" format is particularly realistic. The computer screen is divided into three areas and product profiles are displayed as icons in a "bullpen" on the left. (Bullpen is a term from baseball; relief pitchers wait in the bullpen before being called into the game.) When the consumer rolls a pointing device over an icon, the product and its features are displayed in a middle of the screen. The consumer states whether he or she will consider, not consider, or replace the profile. Considered profiles are displayed to the right

of the screen and the consumer can toggle between considered or not-considered profiles and, at any time, move a profile among the considered, not-considered, or to-be-evaluated sets. See Figure 3 for two examples. After consumers complete a consideration task, we have an observation as to whether or not each product was considered (and a list of aspects describing each product). From these data we seek to infer the decision rule that classifies some products as considered and the remainder as not considered.

[Insert Figure 3 about here.]

Inference Issues. When inferring heuristics researchers face a fit versus complexity tradeoff (Gigerenzer and Brighton 2009; Marewski and Olsson 2009). More complex models have a greater chance of matching heuristics to consideration sets on training data (internal validation), but more-complex models might also exploit random variation and, thus, fit less well on validation data (external validation: Mitchell 1997; Shadish, Cook and Campbell 2002). The following methods have been tested with validation data in which heuristics, estimated from training data, are used to predict consideration sets on subsequent decisions – sometimes after a delay of a week or more. (Most, but not all, cited papers use validation data.)

Heuristics are often evaluated on their ability to predict subsequent consideration decisions. For such decisions, hit rate (percent of decisions predicted correctly) can be misleading because most products are not considered. If only 10% of all products are considered, then a model of "consider nothing" will have a hit rate of 90%. A random model with a 10% consideration probability will have a hit rate of 81% $[(0.90)^2 + (0.10)^2]$. To distinguish models, researchers have begun to use information theory to measure the relative number of bits of information explained by a tested heuristic decision rule (Shannon 1948). This most common measure is a vari-

ation of the Kullback-Leibler (1951) divergence formulated to apply to consideration-set deci-

sions. For example, see Hauser, et al (2010).

Greedoid methods. When a consumer uses a lexicographic heuristic for the consideration

decision, a forward-induction "greedoid" dynamic program can infer an aspect order that is con-

sistent with the most pairwise comparisons (Dieckmann, Dippold and Dietrich 2009; Ding, et al.

2011; Gaskin, et al. 2007; Kohli and Jedidi 2007; Yee, et. al 2007). The algorithm requires 2^M

steps (rather than an exhaustive search of $M!$ rules) and is feasible for problems up to about 20

aspects. Results have varied, but all researchers report that estimated lexicographic decision rules

predict better than additive decision rules for at least some of the consumers. In comparisons

with a q-compensatory model, either lexicographic decision rules predict better (Yee, et al.) or

predict better on average (Ding, et al.2011; Gaskin, et al. 2007).

Bayesian inference. The disjunctive, conjunctive, and subset conjunctive models each im-

ply a data likelihood for observed consideration. See, for example, Jedidi and Kohli (2005, p.

485) for the subset conjunctive model. To estimate disjunctive or conjunctive models researchers

either constrain the Jedidi-Kohli likelihood or modify the Gilbride-Allenby (2004) likelihood to

focus on the consideration-set decision. Hauser, et al (2010) provide examples and comparisons

for a product category described by 16 binary aspects. The advantage of Bayesian methods over

traditional maximum-likelihood methods is that the data likelihood can be specified as a hierar-

chical model in which population information is used to shrink consumer-level parameters to the

population means (implicitly implementing a form of ecological regularity). Although Bayesian

methods are the most common, maximum likelihood, simulated likelihood, or latent-class meth-

ods are also feasible and have been used (e.g. Jedidi and Kohli 2005).

Most applications of Bayesian (and related) methods suggest that consideration-set heuristics predict comparably to additive models and better than q-compensatory models. In comparing heuristics, each inferred by Bayesian methods, results have been mixed. For example, in an application to Handheld Global Positioning Systems (GPSs), the best-predicting heuristic among conjunctive, disjunctive, and subset conjunctive heuristics depends upon the criterion being used to evaluate predictions (Hauser, et al. 2010). The conjunctive heuristic predicted best on a hit-rate criterion and the subset-conjunctive heuristic predicted best on Kullback-Leibler convergence.

Bayesian inference works best when the number of aspects is moderate ($M \leq 20$). Heuristics so estimated predict as well as additive models (Jedidi and Kohli) and sometimes better than q-compensatory models (Hauser, et al. 2010). To the best of our knowledge, Bayesian methods have not been used for $\text{DOC}(S, P)$ models with $S, P > 1$.

Machine learning. Machine learning is particularly suited to the pattern-matching task that is necessary to select the best-fitting heuristic. We are aware of three methods that have been used: logical analysis of data, mathematical programming, and decision trees (Boros, et. al. 1997; 2000; Breiman, et. al. 1984; Currim, Meyer and Le 1988; Evgeniou, Pontil and Toubia 2007; Hastie, Tisbshirani, and Friedman 2003). Machine learning uses an optimization problem to search over rules to find the best-fit and a set of constraints to impose cognitive simplicity and ecological regularity.

For example, logical analysis of data seeks to distinguish "positive" events (consider) from "negative" events (not consider) subject to enforcing cognitive simplicity by limiting the search to at most P patterns of size at most S. A "bottom-up" approach generates minimal pat-

terns of length $s \leq S$ that match some considered profiles. If the patterns are not contained in a non-considered profile, they are retained. The algorithm recursively adds aspects until it generates positive patterns. Next a greedy criterion selects the P positive patterns that fit the data best. When more than one set of patterns fit the data best, logical analysis of data breaks ties by choosing the shortest pattern (cognitive simplicity) and, if patterns are still tied, by choosing patterns that occur most frequently in the observed population (ecological regularity). The net result is a cognitively-simple, ecological-regular, best-fitting $DOC(S, P)$ heuristic. Suitably constrained, logical analysis of data also estimates disjunctive, conjunctive, and subset conjunctive heuristics.

For conjunctive, disjunctive, and subset conjunctive heuristics, predictive abilities of machine-learning methods are comparable to Bayesian inference. Both methods predict well; the comparison between machine learning and Bayesian inference depends upon the heuristic and the product category. In the GPS category, Hauser, et al. (2010) report that $DOC(S, P)$ heuristics predict substantially better than conjunctive, disjunctive, and subset conjunctive heuristics. Interestingly, this best predictive ability is driven by the approximately 7% of the respondents who use more than one conjunction in their heuristic consideration-set screening rules.

Ask Consumers to Describe their Heuristics

Asking consumers to describe their decision rules has a long history in marketing with applications beginning in the 1970s and earlier. Such methods are published under names such as self-explication, direct elicitation, and composition. Reviews include Fishbein and Ajzen (1975), Green (1984), Sawtooth (1996), Hoepfl and Huber (1975), and Wilkie and Pessemier (1973). Some models also include social or personal norms (e.g., Tybout and Hauser 1981). Predictive accuracy based on asking consumers to describe additive rules has varied. Relative comparisons

to inferred additive rules depend upon the product category and upon the specific methods being compared (e.g., Akaah and Korgaonkar 1983; Bateson, Reibstein and Boulding 1987; Green 1984; Green and Helsen 1989; Hauser and Wisniewski 1982; Huber, Wittink, Fiedler, and Miller 1993; Leigh, MacKay and Summers 1984, Moore and Semenik 1988; Reisen, Hoffrage and Mast 2008; Srinivasan and Park 1997).

Until recently, attempts to ask consumers to describe screening heuristics have met with less success because respondents often subsequently choose profiles which have aspects that they have previously said are "unacceptable" (Green, Krieger and Banal 1988; Klein 1986; Srinivasan and Wyner 1988; Sawtooth 1996). Two recent developments have brought these direct-elicitation methods back to the fore: incentive alignment and self-reflection learning.

Incentive alignment. Incentive alignment motivates consumers to think hard and accurately. The consumer must believe that it is in his or her best interests to answer accurately, that there is no obvious way to "game" the system, and that the incentives are sufficient that the rewards to thinking hard exceed the costs of thinking hard. Incentive aligned measures are now feasible, common, and provide data that has proven superior to non-incentive-aligned data (Ding 2007; Ding, Grewal and Liechty 2005; Ding, Park and Bradlow 2009; Park, Ding and Rao 2008; Prelec 2004; Toubia, Hauser and Garcia 2007; Toubia, Simester, Hauser, and Dahan 2003; Toubia, Hauser, and Simester 2004). Researchers commonly reward randomly-chosen respondents with a product from the category about which consumers are asked to state their decision rules. Commonly, the researcher maintains a secret list of available products with a promise to make the list public after the study. The consumer receives a product from the secret list; the specific product is selected by the decision rules that the consumer states.

To measure consideration-set heuristics, incentive alignment is feasible, but requires finesse in carefully-worded instructions. Finesse is required because the consumer receives only one product from the secret list as a prize (Ding, et al. 2011, Hauser, et al. 2010, Kugelberg 2004). For expensive durables incentives are aligned with prize indemnity insurance: researchers buy (publicly available) insurance against the likelihood that a respondent wins a substantial prize such as a $40,000 automobile.

Self-reflection. Stating decision heuristics is difficult. Typically a consumer is asked to state heuristics with little training or warm-up. The consumer is then faced with a real decision, whether it be consideration or choice, and he or she finds that some products are attractive even though they have aspects that the consumer had said were unacceptable. Research suggests that consumers can describe their decision heuristics much better after they make a substantial number of incentive-aligned decisions. For example, in Hauser, Dong, and Ding (2013), the information provided by self-stated decision heuristics, as measured by Kullback-Leibler divergence on decisions made one week later, almost doubled if consumers stated their decision rules after making difficult consideration-set decisions rather than before making consideration-set decisions. Such self-reflection learning is well-established in the adaptive-toolbox literature. Reisen, Hoffrage and Mast (2008) use a method called "Interactive Process Tracing" in which respondents first make decisions and then, retrospectively, interact with an interviewer to describe their decision processes. See related discussions in Betsch, Brinkmann, Fiedler and Breining (1999), Bröder and Newell (2008), Bröder and Schiffer (2006), Garcia-Retamero and Rieskamp (2009), Hansen and Helgeson (1996, 2001), Newell, Rakow, Weston and Shanks (2004), and Rakow, Newell, Fayers and Hersby (2005), among others.

Structured versus unstructured methods. Casemap is perhaps the best-known method to elicit conjunctive decision heuristics (Srinivasan 1988; Srinivasan and Wyner 1988). In Casemap, consumers are presented with each aspect of a product and asked whether or not that aspect is unacceptable. In other structured methods consumers are asked to provide a list of rules that an agent would follow if that agent were to make a consideration-set decision for the consumer. The task is usually preceded by detailed examples of rules that consumers might use. Structured methods have the advantage that they are either coded automatically as in Casemap, or are relatively easy to code by trained coders.

Unstructured methods allow the consumer more flexibility in stating decision rules. For example, one unstructured methods asks the consumer to write an e-mail to an agent who will select a product for the consumer. Instructions are purposefully brief so that the consumer can express him- or herself in his or her own words. Independent coders then parse the statements to identify conjunctive, disjunctive, or compensatory statements. Ding, et al. (2011) provide the following example:

> *Dear friend, I want to buy a mobile phone recently .... The following are some requirement of my preferences. Firstly, my budget is about $2000, the price should not more than it. The brand of mobile phone is better Nokia, Sony-Ericsson, Motorola, because I don't like much about Lenovo. I don't like any mobile phone in pink color. Also, the mobile phone should be large in screen size, but the thickness is not very important for me. Also, the camera resolution is not important too, because i don't always take photo, but it should be at least 1.0Mp. Furthermore, I prefer slide and rotational phone design. It is hoped that you can help me to choose a mobile phone suitable for me.* [0.5 Mp, pink, and small screen were coded as conjunctive (must not have), slide and rotational, and Lenovo

were coded as compensatory. Other statements were judged sufficiently ambiguous and not coded.]

Unstructured methods are relatively nascent, but appear to overcome the tendency of respondents to state too many unacceptable aspects. When coupled with incentive alignment and self-reflection, unstructured methods predict significantly better than structured methods and as well as (for mobile phones) or better than (for automobiles) Bayesian inference and machine-learning methods. Unstructured methods are particularly suitable for product categories with large numbers of aspects $M \gg 20$.

Summary of Recent Developments in Identifying Consideration-Set Heuristics

Managers in product development and marketing have begun to realize the importance of understanding heuristic consideration-set decision rules. To serve those managers, researchers have developed and tested many methods to identify and measure consideration-set heuristics. When only choice data are available, latent methods are the only feasible approaches, but they are limited to either small numbers of aspects (M) or to categories with small numbers of brands (N). When the number of aspects is larger, but still moderate ($M \leq 20$), greedoid methods, Bayesian inference, and machine-learning can each infer decision rules from observed consideration-set decisions. Empirical experience suggests that these methods identify many consumers as using heuristic decision rules and that heuristic models often predict well. The best method appears to depend upon the product category, the decision heuristics being modeled, and researchers' familiarity with the methods. (Future research might enable us to select best methods with greater reliability.) For product categories with large numbers of aspects ($M \gg 20$), such as automobiles, it is now feasible and accurate to ask consumers to state their heuristics directly.

We note one final development. Recently methods have begun to emerge in which consideration-set questions are chosen adaptively (Dzyabura and Hauser 2011; Sawtooth 2008). Adaptive questions maximize the information obtained from each question that the respondent answers. These methods are promising and should relax the aspect limits on inferential methods. For example, Dzyabura and Hauser (2011) estimate conjunctive rules in a category with $M = 53$ aspects. They discuss extensions to DOC rules but have not yet estimated such rules.

7. Example Managerial Applications

Models of additive preferences, known as conjoint analyses, are the most-widely used quantitative marketing research methods, second only to qualitative discussions with groups of consumers (focus groups). Conjoint analyses provide three key inputs to managerial decisions. First, estimated partworths indicate which aspects are most important to which segments of consumers. Product development teams use partworth values to select features for new or revised products and marketing managers use partworth values to select the features to communicate to consumers through advertising, sales force messages, and other marketing tactics. Second, by comparing the relative partworths of product features (aspects) to the relative partworths of price, managers calculate the willingness to pay for features and for the product as a whole. These estimates of willingness to pay help managers set prices for products (as bundles of features) and to set incremental prices for upgrades (say a sunroof on an automobile). Third, a sample of partworths for a representative set of consumers enables managers to simulate how a market will respond to price changes, feature changes, new product launches, competitive entry, and competitive retaliation.

Models of heuristic consideration-set decision rules are beginning to be applied more broadly to provide similar managerial support. These models often modify decisions relative to additive conjoint analyses. Conjunctive (must-have or must-not-have) rules tell managers how to select or communicate product features to maximize the likelihood that consumers will consider a firm's products. For example, Yee, et al. (2007) find that roughly 50% of the consumers rejected a smart phone that was priced in the range of $499; 32% required a flip smart phone; and 29% required a small smart phone. (Recall this was in 2007.)

A sample of heuristic rules from a representative set of consumers enables managers to simulate feature changes, new product launches, competitive entry, and competitive retaliation. For example, Ding, et al. (2011) simulates how young Hong Kong consumers would respond to new mobile telephones. They project that "if Lenovo were considering launching a $HK2500, pink, small-screen, thick, rotational phone with a 0.5 megapixel camera resolution, the majority of young consumers (67.8%) would not even consider it. On the other hand, almost everyone (all but 7.7%) would consider a Nokia, $HK2000, silver, large-screen, slim, slide phone with 3.0 megapixel camera resolution." If price is included as an aspect in the heuristic rules (as it often is), heuristic-based simulators estimate the numbers of consumers who will screen out a product at a given price point or estimate the number of consumers who will consider a product because it has an attractive price.

In many cases, heuristic-rule summaries and simulators provide information that complements additive-partworth simulators. However, there are instances where managerial implications are different. For example, Gilbride and Allenby (2004, 400) report that, for cameras, price and body style play an important role in the consideration-set decision, but not in the final choice from among considered products. Jedidi and Kohli (2005, 491) provide examples in the market

for personal computers where, because price is used as an aspect in a screening heuristic, market share predictions vary by as much as a factor of two (16% vs. 36%) between simulators. They obtain quite different predictions with a subset-conjunctive-rule simulator versus an additive-rule simulator for many marketing decisions. For example, a subset-conjunctive-rule simulator predicts that one brand will gain14% in market share due to a price reduction. The corresponding prediction based on estimated additive rules is twice as much.

Hauser, et al (2010) provide two examples. One of the GPS brands, Magellan, has, on average, slightly higher brand partworths, but 12% of the consumers screen on brand and 82% of those consumers must have the Garmin brand. As a result, $DOC(S, P)$-based analysis predicts that Garmin is substantially less sensitive to price changes than would be predicted by an additive-partworth analysis. In a second example, "additive rules predict that an 'extra bright' display is the highest-valued feature improvement yielding an 11% increase for the $50 incremental price. However, $DOC(S, P)$ rules predict a much smaller improvement (2%) because many of the consumers who screen on 'extra bright' also eliminate GPSs with the higher price."

Finally, Urban and Hauser (2004) "listen in" on web-based advisors to identify sets of aspects that consumers would consider, but which are not now available on the market. For example, they identified opportunities for a maneuverable full-sized truck, a compact truck that could tow and haul heavy materials, and a full-sized truck with a six-cylinder engine. The first opportunity, worth an estimated $2.4-3.2 million in incremental truck sales, was made feasible with four-wheel steering.

To date, these examples are illustrative. We do not yet have general guidelines to indicate which method is best in which situation. However, we do recommend that researchers test for

non-compensatory decisions whenever they undertake conjoint analyses for managerial applications.

8. Discussion and Summary

Research on decision making has led to insights about the decision rules that consumers use when deciding which products (and services) to consider for eventual purchase. Evidence is strong that consumers first limit product evaluations to consideration sets and often do so with heuristic decision rules. Heuristic decision rules screen products efficiency and, when used, are rational because they often represent the best tradeoff between the benefit from considering more products and the cost of searching for and evaluating information on those products. Because consider-then-choose heuristics describe consumer behavior, it is not surprising that predicted outcomes (considered products or chosen products) depend upon whether or not these heuristics are modeled accurately. Not every managerial decision will change if heuristic decision-rule models rather than additive models are used, but many will.

In response to managerial need, the past few years have led to the explosion of practical measurement and estimation methods to infer consideration-set heuristics. It is now feasible to develop accurate models based on either observing consumers' consideration sets or asking consumers (with aligned incentives and self-reflection) to state their heuristic decision rules. The models do well on validation tests; they often predict as well as or better than traditional additive or q-compensatory models. While not all consumers in all categories are described best by consideration-set heuristics, evidence is compelling that many consumers are best described by these models. We expect the performance of these models to improve with further application. (For example, the leading supplier of software for "conjoint analysis" now incorporates the measure-

ment of consideration-set heuristics in "adaptive choice-based conjoint analysis.") We also expect that further application and further research will lead to a better understanding of which models are best for which product categories and which managerial decisions. Many research and application challenges lie ahead, but we are optimistic that these challenges will be met.

References

Akaah, I. P. and P. K. Korgaonkar (1983). An empirical comparison of the predictive validity of self-explicated, huber-hybrid, traditional conjoint, and hybrid conjoint models, *Journal of Marketing Research*, 20, (May), 187-197.

Andrews, R. L. and T. C. Srinivasan (1995). Studying consideration effects in empirical choice models using scanner panel data, *Journal of Marketing Research*, 32, (February), 30-41.

Bateson, J. E. G., D. Reibstein, and W. Boulding (1987). Conjoint analysis reliability and validity: a framework for future research, *Review of Marketing*, Michael Houston, Ed., pp. 451-481.

Betsch, T., B. J. Brinkmann, K. Fiedler and K. Breining (1999). When prior knowledge overrules new evidence: adaptive use of decision strategies and the role of behavioral routines, *Swiss Journal of Psychology*, 58, 3, 151-160.

Bettman, J. R. and L. W. Park (1980). Effects of prior knowledge and experience and phase of the choice process on consumer decision processes: a protocol analysis, *Journal of Consumer Research*, 7, 234-248.

Bettman, J. R., M. F. Luce and J. W. Payne (1998). Constructive consumer choice processes, *Journal of Consumer Research*, 25, (December), 187-217.

Boros, E., P. L. Hammer, T. Ibaraki, and A. Kogan (1997). Logical analysis of numerical data, *Mathematical Programming*, 79, (August), 163-190.

Boros, E., P. L. Hammer, T. Ibaraki, and A. Kogan, E. Mayoraz, and I. Muchnik (2000). An implementation of logical analysis of data, *IEEE Transactions on Knowledge and Data Engineering*, 12, 2, 292-306.

Brandstaetter, E., G. Gigerenzer and R. Hertwig (2006). The Priority heuristic: making choices without trade-offs, *Psychological Review*, 113, 409-432.

Breiman, L., J. H. Friedman, R. A. Olshen, and C. J. Stone (1984). *Classification and regression trees*, Belmont, CA: Wadsworth.

Brighton, H. (2006). Robust inference with simple cognitive models, In: Lebiere, C. and Wray, R. (Eds.) *AAAI spring symposium: Cognitive science principles meet AI-hard problems.* Menlo Park, CA: American Association for Artificial Intelligence, 17-22.

Bröder, A. (2000). Assessing the empirical validity of the "take the best" heuristic as a model of human probabilistic inference, *Journal of Experimental Psychology: Learning, Memory, and Cognition,* 26, 5, 1332-1346.

Bröder, A. and A. Eichler (2006). The use of recognition information and additional cues in inferences from memory. *Acta Psychologica*, 121, 275–284.

Bröder, A. and W. Gaissmaier (2007). Sequential processing of cues in memory-based multiattribute decisions, *Psychonomic Bulletin & Review*, 14, 5, 895-900.

Bröder, A. and B. R. Newell (2008). Challenging some common beliefs: empirical work within the adaptive toolbox metaphor, *Judgment and Decision Making*, 3, 3, (March), 205-214.

Bröder, A. and S. Schiffer (2006). Adaptive flexibility and maladaptive routines in selecting fast and frugal decision strategies, *Journal of Experimental Psychology: Learning, Memory and Cognition*, 34, 4, 908-915.

Bronnenberg, B. J., and W. R. Vanhonacker (1996). Limited choice sets, local price response, and implied measures of price competition, *Journal of Marketing Research*, 33, (May), 163-173.

Brown, J. J. and A. R. Wildt (1992). Consideration set measurement, *Journal of the Academy of Marketing Science*, 20, 3, 235-263.

Chase, V. M., R. Hertwig, and G. Gigerenzer (1998). Visions of rationality, *Trends in Cognitive Science*s, 2, 6, (June), 206-214.

Chiang, J., S. Chib and C. Narasimhan (1999). Markov chain Monte Carlo and models of consideration set and parameter heterogeneity, *Journal of Econometrics*, 89, 223-248.

Chu, P.C. and E. E. Spires (2003). Perceptions of accuracy and effort of decision strategies, *Organizational Behavior and Human Decision Processes*, 91, 203-14.

Coates, S. L., L. T. Butler and D. C. Berry (2004). Implicit memory: a prime example for brand consideration and choice, *Applied Cognitive Psychology*, 18, (June), 1195-1211.

Coates, S. L., L. T. Butler and D. C. Berry (2006). Implicit memory and consumer choice: the mediating role of brand familiarity, *Applied Cognitive Psychology*, 20, (July), 1101-1116.

Cucker, F., and Steve S. (2002). On the mathematical foundations of learning, *Bulletin of the American Mathematical Society*, 39, 1, 1-49.

Currim, I. S., R. J. Meyer, and N. T. Le (1988). Disaggregate tree-structured modeling of consumer choice data, *Journal of Marketing Research*, 25, (August), 253-265.

Dawes, R. M. (1979). The robust beauty of improper linear models in decision making, *American Psychologist*, 34, 7, (July), 571-582.

Dawkins, R. (1998). *Unweaving the rainbow: science, delusion, and the appetite for wonder*, Boston, MA: Houghton Mifflin Company.

DeSarbo, W. S., D. R. Lehmann, G. Carpenter, and I. Sinha (1996). A Stochastic multidimensional unfolding approach for representing phased decision outcomes, *Psychometrika*, 61, 3, 485-508.

Dieckmann, A., K. Dippold and H. Dietrich (2009). Compensatory versus noncompensatory models for predicting consumer preferences, *Judgment and Decision Making*, 4, 3, (April), 200-213.

Ding, M. (2007). An incentive-aligned mechanism for conjoint analysis, *Journal of Marketing Research*, 54, (May), 214-223.

Ding, M., R. Grewal, and J. Liechty (2005). Incentive-aligned conjoint analysis, *Journal of Marketing Research*, 42, (February), 67–82.

Ding, M., J. R. Hauser, S. Dong, D. Dzyabura, Z. Yang, C. Su, and S. Gaskin (2011). Unstructured direct elicitation of decision rules, *Journal of Marketing Research*, 48, (February), 116-127.

Ding, M., Y-H. Park, and E. T. Bradlow (2009) Barter markets for conjoint analysis *Management Science*, 55, 6, 1003-1017.

Dzyabura, D. and J. R. Hauser (2011). Active machine learning for consideration heuristics, *Marketing Science*, 30, 5, (September-October), 801-819.

Einhorn, H. J. (1970). The use of nonlinear, noncompensatory models in decision making, *Psychological Bulletin*, 73, 3, 221-230.

Einhorn, H. J. (1971). Use of non-linear, non-compensatory models as a function of task and amount of information, *Organizational Behavior and Human Performance*, 6, 1-27.

Einhorn, H. J. and R. M. Hogarth (1975). Unit weighting schemes for decision making, *Organizational Behavior and Human Performance*, 13, 171-192.

Einhorn, H. J. and R. M. Hogarth (1981). Behavioral decision theory: processes of judgment and choice, *Annual Review of Psychology*, 32, 52-88.

Erdem, T. and J. Swait (2004). Brand credibility, brand consideration, and choice, *Journal of Consumer Research*, 31, (June), 191-98.

Evgeniou, T., C. Boussios, and G. Zacharia (2005). Generalized robust conjoint estimation, *Marketing Science*, 24, 3, 415-429.

Evgeniou, T., M. Pontil, and O. Toubia (2007). A convex optimization approach to modeling heterogeneity in conjoint estimation, *Marketing Science*, 26, 6, (Nov.-Dec.), 805-818.

Fader, P. S. and L. McAlister (1990). An elimination by aspects model of consumer response to promotion calibrated on UPC scanner data, *Journal of Marketing Research,* 27, (August), 322-32.

Fishbein, M. and I. Ajzen (1975). *Belief, attitude, intention, and behavior*, Reading, MA: Addison-Wesley.

Fishburn, P. C. (1974). Lexicographic orders, utilities and decision rules: a survey, *Management Science*, 20, 11, (Theory, July), 1442-1471.

Frederick, S. (2002). Automated choice heuristics, in T Gilovich, D. Griffin, and D. Kahneman, eds., *Heuristics and Biases: The Psychology of Intuitive Judgment*, Cambridge, UK: Cambridge University Press, chapter 30, 548-558.

Frosch, C. A., C. P. Beaman and R. McCloy (2007). A little learning is a dangerous thing: an experimental demonstration of recognition-driven inference, *The Quarterly Journal of Experimental Psychology*, 60, 1329–1336.

Ganzach, Y. and B. Czaczkes (1995). On detecting nonlinear noncompensatory judgment strategies: comparison of alternative regression models, *Organizational Behavior and Human Decision Processes*, 61, (February), 168-76.

Garcia-Retamero, R. and J. Rieskamp (2009). Do people treat missing information adaptively when mak-

ing inferences?, *Quarterly Journal of Experimental Psychology*, 62, 10, 1991-2013.

Gaskin, S., T. Evgeniou, D. Bailiff, and J. R. Hauser (2007). Two-stage models: identifying non-compensatory heuristics for the consideration set then adaptive polyhedral methods within the consideration set, *Proceedings of the Sawtooth Software Conference*, Santa Rosa, CA, October 17-19, 2007.

Gensch, D. H. (1987). A two-stage disaggregate attribute choice model, *Marketing Science*, 6, (Summer), 223-231.

Gensch, D. H. and E. S. Soofi (1995a). Information-theoretic estimation of individual consideration sets, *International Journal of Research in Marketing*, 12, (May), 25-38.

Gensch, D. H. and E. S. Soofi (1995b). An information-theoretic two-stage, two-decision rule, choice model, *European Journal of Operational Research*, 81, 271-80.

Gigerenzer, G. and H. Brighton (2007). Can hunches be rational?, *Journal of Law, Economics, and Policy,* 4, 155-175.

Gigerenzer, G. and H. Brighton (2009). Homo Heuristicus: why biased minds make better inferences, *Topics in Cognitive Science*, 1, 107-143.

Gigerenzer, G. and D. G. Goldstein (1996). Reasoning the fast and frugal way: models of bounded rationality, *Psychological Review*, 103, 4, 650-669.

Gigerenzer, G. U. Hoffrage, and H. Kleinbölting (1991). Probabilistic mental models: a Brunswikian theory of confidence, *Psychological Review*, 98, 506-528.

Gigerenzer, G. and R. S., Editors (2001). *Bounded rationality: the adaptive toolbox*, Cambridge, MA: The MIT Press.

Gigerenzer, G., P. M. Todd, and the ABC Research Group (1999). *Simple heuristics that make us smart*,

Oxford, UK: Oxford University Press.

Gilbride, T. and G. M. Allenby (2004). A choice model with conjunctive, disjunctive, and compensatory screening rules, *Marketing Science*, 23, 3, (Summer), 391-406.

Gilbride, T. and G. M. Allenby (2006). Estimating heterogeneous eba and economic screening rule choice models, *Marketing Science*, 25, (September-October), 494-509.

Gittins, J. C. (1979). Bandit processes and dynamic allocation indices, *Journal of the Royal Statistical Society, Series B (Methodological)*, 41, 2, 148-177, plus commentary.

Goldstein, D. G., and G. Gigerenzer (1999). The recognition heuristic: how ignorance makes us smart, In G. Gigerenzer, P. M. Todd, & the ABC Research Group, *Simple Heuristics That Make Us Smart*, New York, NY: Oxford University Press.

Goldstein, D. G., and G. Gigerenzer (2002). Models of ecological rationality: the recognition heuristic, *Psychological Review*, 109, 1, 75-90.

Green, P. E., (1984). Hybrid models for conjoint analysis: an expository review, *Journal of Marketing Research*, 21, (May), 155-169.

Green, P. E. and K. Helsen (1989). Cross-validation assessment of alternatives to individual-level conjoint analysis: A Case Study, *Journal of Marketing Research*, 26, (August), 346-350.

Green, P. E., A. M. Krieger, and P. Bansal (1988). Completely unacceptable levels in conjoint analysis: a cautionary note, *Journal of Marketing Research*, 25, (August), 293-300.

Gross, I. (1972). The creative aspects of advertising, *Sloan Management Review*, 14, (Fall), 83-109.

Gumbel, E. J. (1958). *Statistics of extremes*, New York, NY: Columbia University Press.

Hastie, T., R. Tibshirani, J. H. Friedman (2003). *The elements of statistical learning*, New York, NY:

Springer Series in Statistics.

Hansen, D. E. and J. G. Helgeson (1996). The effects of statistical training on choice heuristics in choice under uncertainty, *Journal of Behavioral Decision Making*, 9, 41-57.

Hansen, D. E. and J. G. Helgeson (2001). Consumer response to decision conflict from negatively correlated attributes: down the primrose path of up against the wall?, *Journal of Consumer Psychology*, 10, 3, 159-169.

Hauser, J. R. (1978). Testing the accuracy, usefulness and significance of probabilistic models: an information theoretic approach, *Operations Research*, 26, 3, (May-June), 406-421.

Hauser, J. R. (1986). Agendas and consumer choice, *Journal of Marketing Research*, 23, (August), 199-212.

Hauser, J. R., S. Dong, and M. Ding (2013). Self-reflection and articulated consumer preferences, forthcoming, *Journal of Product Innovation Management*.

Hauser, J. R., O. Toubia, T. Evgeniou, D. Dzyabura, and R. Befurt (2010). Cognitive simplicity and consideration sets, *Journal of Marketing Research*, 47, (June), 485-496.

Hauser, J. R., G. L. Urban, and G. Liberali (2013). When to Morph: theory and field test of website morphing 2.0, (Cambridge, MA: MIT Sloan School of Management), March.

Hauser, J. R. and B. Wernerfelt (1990). An evaluation cost model of consideration sets, *Journal of Consumer Research*, 16, (March), 393-408.

Hauser, J. R. and K. J. Wisniewski (1982). Dynamic analysis of consumer response to marketing strategies, *Management Science*, 28, 5, (May), 455-486.

Hoepfl, R. T. and G. P. Huber (1970). A study of self-explicated utility models, *Behavioral Science*, 15, 408-414.

Hogarth, R. M. and N. Karelaia (2005). Simple models for multiattribute choice with many alternatives: when it does and does not pay to face trade-offs with binary attributes, *Management Science*, 51, 12, (December), 1860-1872.

Huber, J., D. R. Wittink, J. A. Fiedler, and R. Miller (1993). The effectiveness of alternative preference elicitation procedures in predicting choice, *Journal of Marketing Research*, 30, (February), 105-114.

Hutchinson, J. M. C. and G. Gigerenzer (2005). Simple heuristics and rules of thumb: where psychologists and behavioural biologists might meet, *Behavioural Processes*, 69, 97-124.

Janiszewski, C. (1993). Preattentive mere exposure effects, *Journal of Consumer Research*, 20, (December), 376-392.

Jedidi, K. and R. Kohli (2005). Probabilistic subset-conjunctive models for heterogeneous consumers, *Journal of Marketing Research*, 42, 4, 483-494.

Jedidi, K., R. Kohli and Wayne S. DeSarbo (1996). Consideration sets in conjoint analysis, *Journal of Marketing Research*, 33, (August), 364-372.

Johnson, E. J., R. J. Meyer, and S. Ghose (1989). When choice models fail: compensatory models in negatively correlated environments, *Journal of Marketing Research*, 26, (August), 255-290.

Johnson, E. J. and J. W. Payne (1985). Effort and accuracy in choice, *Management Science*, 31, 395-414.

Klein, N. M. (1988). Assessing unacceptable attribute levels in conjoint analysis, *Advances in Consumer Research*, 14, 154-158.

Kohli, R. and K. Jedidi (2007). Representation and inference of lexicographic preference models and their variants, *Marketing Science*, 26, (May-June), 380-99.

Kugelberg, E. (2004). Information scoring and conjoint analysis, Department of Industrial Economics and

Management, Royal Institute of Technology, Stockholm, Sweden.

Kullback, S., and R. A. Leibler (1951). On information and sufficiency, *Annals of Mathematical Statistics,* 22, 79-86.

Langley, P. (1996). *Elements of machine learning*, San Francisco, CA: Morgan Kaufmann.

Lenk, P. J., W. S. DeSarbo, P. E. Green, and M. R. Young (1996). Hierarchical Bayes conjoint analysis: recovery of partworth heterogeneity from reduced experimental designs, *Marketing Science*, 15, 2, 173-191.

Leigh, T. W., D. B. MacKay, and J. O. Summers (1984). Reliability and validity of conjoint analysis and self-explicated weights: a comparison, *Journal of Marketing Research*, 21, 4, (November), 456-462.

Leven, S. J. and D. S. Levine (1996). Multiattribute decision making in context: a dynamic neural network methodology, *Cognitive Science*, 20, 271-299.

Liberali, G., G. L. Urban, and J. R. Hauser (2013). Competitive information, trust, brand consideration, and sales: two field experiments *International Journal for Research in Marketing*, 30, 2, (June), 101-113.

Lichtenstein, S. and P. Slovic (2006). *The construction of preference*, Cambridge, UK: Cambridge University Press.

Lohse, G. J. and E. J. Johnson (1996). A comparison of two process tracing methods for choice tasks, *Organizational Behavior and Human Decision Processes*, 68, (October), 28-43.

Lussier, D. A. and R. W. Olshavsky (1997). Task complexity and contingent processing in brand choice, *Journal of Consumer Research*, 6, (September), 154-65.

Lynch, J. G. and T. K. Srull (1982). Memory and attentional factors in consumer choice: concepts and re-

search methods, *Journal of Consumer Research*, 9, 1, (June), 18–36.

Marewski, J. N., W. Gaissmaier and G. Gigerenzer (2010). Good Judgments do not require complex cognition, *Cognitive Processing*, 11, 103-121.

Marewski, J. N., W. Gaissmaier, L. J. Schooler, D. G. Goldstein, and G. Gigerenzer (2010). From recognition to decisions: extending and testing recognition-based models for multi-alternative inference, *Psychonomic Bulletin and Review* (Theory & Review Section), 27, 287-309.

Marewski, J. N. and H. Olsson (2009). Beyond the null ritual: formal modeling of psychological processes, *Journal of Psychology,* 217, 1, 49-60.

Martignon, L. (2001). Comparing fast and frugal heuristics and optimal models, in G. Gigerenzer and R. Selten, Editors (2001), *Bounded Rationality: The Adaptive Toolbox*, Cambridge, MA: The MIT Press.

Martignon, L. and U. Hoffrage (2002). Fast, frugal, and fit: simple heuristics for paired comparisons, *Theory and Decision*, 52, 29-71.

Mehta, N., S. Rajiv, and K. Srinivasan (2003). Price uncertainty and consumer search: a structural model of consideration set formation, *Marketing Science*, 22, 1, 58-84.

Mela, C. F. and D. R. Lehmann (1995). Using fuzzy set theoretic techniques to identify preference rules from interactions in the linear model: an empirical study, *Fuzzy Sets and Systems*, 71, 165-181.

Mitchell, T. M. (1997). *Machine learning*, Boston MA: WCB McGraw-Hill.

Moe, W. W. (2006). An empirical two-stage choice model with varying decision rules applied to internet clickstream data, *Journal of Marketing Research*, 43, (November), 680-692.

Montgomery, H. and O. Svenson (1976). On decision rules and information processing strategies for choices among multiattribute alternatives, *Scandinavian Journal of Psychology,* 17, 283-291.

Moore, W. L. and R. J. Semenik (1988). Measuring preferences with hybrid conjoint analysis: the impact of a different number of attributes in the master design, *Journal of Business Research*, 16, 3, (May), 261-274.

Nakamura, Y. (2002). Lexicographic quasilinear utility, *Journal of Mathematical Economics*, 37, 157-178.

Nedungadi, P. (1990). Recall and consumer consideration sets: influencing choice without altering brand evaluations, *Journal of Consumer Research*, 17, (December), 263-276.

Newell, B. R., T. Rakow, N. J. Weston and D. R. Shanks (2004). Search strategies in decision-making: the success of success, *Journal of Behavioral Decision Making*, 17, 117-137.

Olshavsky, R. W. and F. Acito (1980). An information processing probe into conjoint analysis, *Decision Sciences*, 11, (July), 451-470.

Ozer, M. (1999). A survey of new product evaluation models, *Journal of Product Innovation Management*, 16, (January), 77–94.

Park, Y-H., M. Ding and V. R. Rao (2008). Eliciting preference for complex products: a web-based upgrading method, *Journal of Marketing Research*, 45, (October), 562-574.

Paulssen, M. and R. P. Bagozzi (2005). A self-regulatory model of consideration set formation, *Psychology & Marketing*, 22, (October), 785-812.

Payne, J. W. (1976). Task complexity and contingent processing in decision making: an information search, *Organizational Behavior and Human Performance*, 16, 366-387.

Payne, J. W., J. R. Bettman, and E. J. Johnson (1988). Adaptive strategy selection in decision making, *Journal of Experimental Psychology: Learning, Memory, and Cognition,* 14, 534-552.

Payne, J. W., J. R. Bettman, and E. J. Johnson (1993). *The adaptive decision maker*, Cambridge, UK:

Cambridge University Press.

Prelec, D. (2004). A Bayesian truth serum for subjective data, *Science*, 306, (October 15), 462-466.

Punj, G. and R. Brookes (2001). Decision constraints and consideration-set formation in consumer durables, *Psychology & Marketing*, 18, 8, (August), 843-863.

Punj, G. and R. Staelin (1983). A model of consumer information search behavior for new automobiles, *Journal of Consumer Research*, 9, 366-380.

Rakow, T., B. R. Newell, K. Fayers and M. Hersby (2005). Evaluating three criteria for establishing cue-search hierarchies in inferential judgment, *Journal Of Experimental Psychology-Learning Memory And Cognition*, 31, 5, 1088-1104.

Reisen, N., U. Hoffrage and F. W. Mast (2008). Identifying decision strategies in a consumer choice Situation, *Judgment and Decision Making*, 3, 8, (December), 641-658.

Roberts, J. H., and J. M. Lattin (1991). Development and testing of a model of consideration set composition, *Journal of Marketing Research*, 28, (November), 429-440.

Rossi, P. E., and G. M. Allenby (2003). Bayesian statistics and marketing, *Marketing Science*, 22, 3, 304-328.

Sawtooth Software, Inc. (1996). ACA system: adaptive conjoint analysis, ACA Manual, Sequim, WA: Sawtooth Software, Inc.

Sawtooth Software, Inc. (2008). ACBC technical paper, Sequim WA; Sawtooth Software, Inc.

Shadish, W. R., T. D. Cook and D. T. Campbell (2002). *Experimental and quasi-experimental designs for generalized causal inference*, Boston, MA: Houghton Mifflin Company.

Shannon, C.E. (1948). A mathematical theory of communication, *Bell System Technical Journal*, 27, (Ju-

ly & October), 379–423 & 623–656.

Shao, J. (1993). Linear model selection by cross-validation, *Journal of the American Statistical Association*, 88, 422, (June), 486-494.

Shocker, A. D., M. Ben-Akiva, B. Boccara, and P. Nedungadi (1991). Consideration set influences on consumer decision-making and choice: issues, models, and suggestions, *Marketing Letters*, 2, 3, 181-197.

Shugan, S. M. (1980). The cost of thinking, *Journal of Consumer Research*, 27, 2. 99-111.

Silk, A. J. and G. L. Urban (1978). Pre-test market evaluation of new packaged goods: a model and measurement methodology, *Journal of Marketing Research*, 15, (May), 171-191.

Simon, H. A. (1967). Motivation and emotional controls of cognition, *Psychological Review*, 74, 1, 29-39.

Srinivasan, V. (1988). A conjunctive-compensatory approach to the self-explication of multiattributed preferences, *Decision Sciences*, 19, 2, (June), 295-305.

Srinivasan, V. and C. S. Park (1997). Surprising robustness of the self-explicated approach to customer preference structure measurement, *Journal of Marketing Research*, 34, (May), 286-291.

Srinivasan, V. and G. A. Wyner (1988). Casemap: computer-assisted self-explication of multiattributed preferences, in W. Henry, M. Menasco, and K. Takada, Eds, *Handbook on New Product Development and Testing*, Lexington, MA: D. C. Heath, 91-112.

Stigler, G. J. (1961). The economics of information, *J. of Political Economy*, 69, (June), 213-225.

Svenson, O. (1979). Process descriptions of decision making, *Organizational Behavior and Human Performance*, 23, 86-112.

Swait, J. (2001). A noncompensatory choice model incorporating cutoffs, *Transportation Research*, 35, Part B, 903-928.

Swait, J. and M. Ben-Akiva (1987). Incorporating random constraints in discrete models of choice set generation, *Transportation Research*, 21, Part B, 92-102.

Thorngate, W. (1980). Efficient decision heuristics, *Behavioral Science*, 25, (May), 219-225.

Toubia, O., D. I. Simester, J. R. Hauser, and E. Dahan (2003). Fast polyhedral adaptive conjoint estimation, *Marketing Science*, 22, 3, 273-303.

Toubia, O., J. R. Hauser and R. Garcia (2007). Probabilistic polyhedral methods for adaptive choice-based conjoint analysis: theory and application, *Marketing Science*, 26, 5, (September-October), 596-610.

Toubia, O., J. R. Hauser, and D. Simester (2004). Polyhedral methods for adaptive choice-based conjoint analysis, *Journal of Marketing Research*, 41, 1, (February), 116-131.

Tybout, A. M. and J. R. Hauser (1981). "A marketing audit using a conceptual model of consumer behavior: application and evaluation," *Journal of Marketing*, 45, 3, (Summer), 81-101.

Tversky, A. (1969). Intransitivity of preferences, *Psychological Review*, 76, 31-48.

Tversky, A. (1972). Elimination by aspects: a theory of choice, *Psychological Review*, 79, 4, 281-299.

Tversky, A. and S. Sattath (1979). Preference trees, *Psychological Review*, 86, 6, 542-573.

Tversky, A. and I. Simonson (1993). Context-dependent preferences, *Management Science*, 39, (October), 1179-1189.

Urban, G. L. and J. R. Hauser (1993). *Design and marketing of new products, 2E*, Englewood Cliffs, NJ: Prentice-Hall.

Urban, G. L. and J. R. Hauser (2004). "Listening-in" to find and explore new combinations of customer

needs, *Journal of Marketing*, 68, (April), 72-87.

Urban, G. L. and G. M. Katz (1983). Pre-test market models: validation and managerial implications, *Journal of Marketing Research*, 20, (August), 221-34.

van Nierop, E., B. Bronnenberg, R. Paap, M. Wedel, and P. H. Franses (2010). Retrieving unobserved consideration sets from household panel data, *Journal of Marketing Research*, 47, (February), 63-74.

Vapnik, V. (1998). *Statistical learning theory*, New York, NY: John Wiley and Sons.

Vroomen, B., P. H. Franses and E. van Nierop (2004). Modeling consideration sets and brand choice using artificial neural networks, *European Journal of Operational Research*, 154, 206-217.

Wilkie, W. L. and E. A. Pessemier (1973). Issues in marketing's use of multi-attribute attitude models, *Journal of Marketing Research*, 10, (November), 428-441.

Wright, P. and F. Barbour (1977). Phased decision making strategies: sequels to an initial screening, *TIMS Studies in the Management Sciences*, 6, 91-109

Wu, J. and A. Rangaswamy (2003). A fuzzy set model of search and consideration with an application to an online market, *Marketing Science*, 22, (Summer), 411-434.

Yee, M., E. Dahan, J. R. Hauser, and J. Orlin (2007). Greedoid-based noncompensatory inference, *Marketing Science*, 26, (July-August), 532-549.

Zajonc, R. B. (1968). Attitudinal effects of mere exposure, *Journal of Personality and Social Psychology*, 9, 2, Part 2, (June), 1-27.

Figure 1

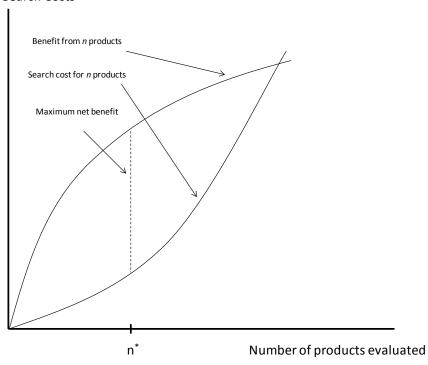Consideration Sets are Rational

Benefit or Search Costs

Benefit from *n* products

Search cost for *n* products

Maximum net benefit

n^*

Number of products evaluated

Figure 2

Decision Heuristics are Rational

Benefit or Search Costs

Benefit from *n* products
heuristic evaluation

Benefit from *n* products
complete evaluation

Search cost for *n* products
complete evaluation

Maximum net benefit
complete evaluation

Maximum net benefit
heuristic evaluation

Search cost for *n* products
heuristic evaluation

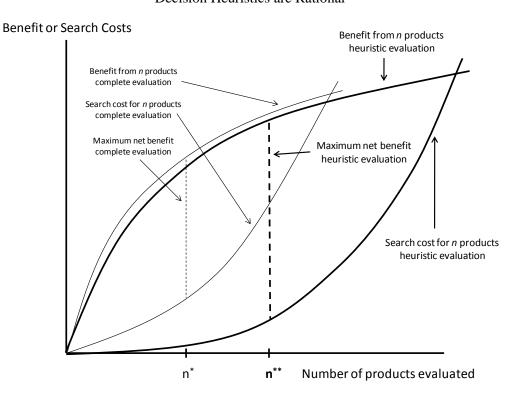n^* n^{**} Number of products evaluated

Figure 3

Example Online Measurement of a Consideration Set

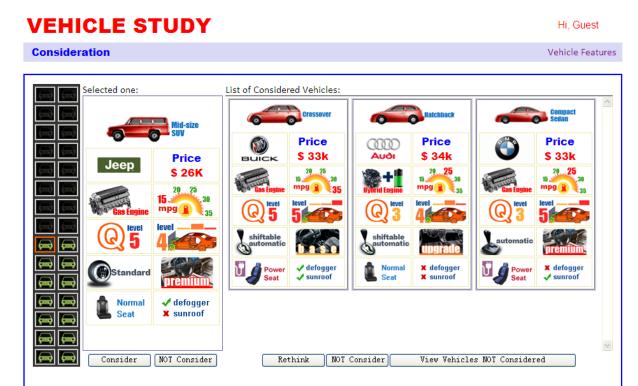**(as used by Ding, et al. 2011 and Hauser, et al. 2010)**

Table 1. Example Heuristic (and Compensatory) Decision Rules

Rule Type	Decision Rule	Description of Decision Rule	Example for Vehicle Consideration
Non-compensatory		It may not be possible for other aspects to compensate for the presence or absence of an aspect.	Use a rule to distinguish considered from not considered vehicles. All aspects need not be evaluated.
	Conjunctive	Consider if the product has all "must have" and has no "must not have" aspects.	Consider if sporty coupe with a sunroof, not black, white or silver, stylish, well-handling, moderate fuel economy, AND moderately priced.
	Disjunctive	Consider if the product has one or more "excitement" aspects.	Consider if sporty coupe OR if moderate fuel economy
	Lexicographic by aspects	Rank aspects. Rank products on top-ranked aspect, then second-ranked aspect and so on. Consider the first top-ranked n^* products	Rank on sporty coupe, of those rank on sunroof, of those rank on color continuing vehicles ranked on relevant aspects. Consider the top-ranked n^* vehicles.
	Elimination by aspects	Rank aspects. Eliminate all products that do not have top-ranked aspect, then second-ranked aspect, and so on until only n^* products are left to consider.(Deterministic version.)	Eliminate non-sporty vehicles, then eliminate non-coupes, then eliminate vehicles that are not stylish, and so on.
	Take the best	Rank products on the aspect that best discriminates consider from not consider. Consider all products with that aspect.	If sporty is the most diagnostic aspect, consider only sporty vehicles.
	Subset conjunctive	Consider if the product has S "must have" aspects.	Consider if 5 of the following aspects are satisfied: sporty, coupe, sunroof, not black, not white, not silver, well-handling, moderate fuel economy, moderately priced.
	Disjunctions of conjunctions	Consider if the product has (does not have) one or more sets of "must have" ("must not have") aspects.	Consider if well-handling sporty coupe with a sunroof OR sporty coupe with moderate fuel economy
Compensatory		One or more aspects can compensate for the lack of another aspect.	Compute an index. Consider n^* vehicles with a value above a cutoff on this index.
	Additive	"Utility" is an additive function of the "partworths" for each aspect. Consider n^* products above a threshold.	Determine a partworth for each potential automotive aspect and add all partworths corresponding to the aspects that the vehicle has.
	Equal weights	"Utility" is a sum of the feature values. Usually applied when features are continuous as in "miles per gallon" or scaled judgments such as "handling ability."	For continuous features such as miles per gallon, speed, and price, add the feature values (assuming reasonable scaling of units).
	Linear	"Utility" is a weighted sum of the feature values. Usually applied when features are continuous as in "miles per gallon" or scaled judgments such as "handling ability."	For continuous features such as miles per gallon, speed, leg-room, and price, compute a weighted average of the feature values.
	Tallying	When all aspects are binary, count the positive aspects.	For binary features such as "has or does not have a sunroof," count the number of positive features in the vehicle.