

NON-COMPENSATORY (AND COMPENSATORY) MODELS OF CONSIDERATION-SET DECISIONS

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WHY STUDY CONSIDERATION SETS

If customers do not consider your product, they can't choose it. There is evidence that 80% of the uncertainty in choice models can be explained by simply knowing the consideration set (Hauser 1978). Many important managerial decisions rely on identifying how customers form consideration sets: Which features lead customers to eliminate certain products from further consideration? Which features lead customers to seek further information and thus open the opportunity for a sale? How do technical specifications and quantifiable features of a product interact with more qualitative features such as service or reliability? Does "brand" drive consideration? And what can a firm do about it?

This problem is real. Even though a Buick was tied in 2008 with Lexus as the top-ranked automobile on a J. D. Power dependability study, was the top-ranked American car by *Consumer Reports*, and produced cars from the top-ranked US factory for quality, in 2008 few US consumers would even consider a Buick – in California almost two-thirds of consumers rejected GM cars without evaluating them; nationwide the percentage was closer to 50%. Investments in reliability, quality, safety, ride and handling, comfort, navigation, interiors, and Onstar become irrelevant if consumers never get beyond the consideration stage. For this and other reasons, the US automobile manufacturers were considering or entering bankruptcy in the spring of 2009.

Autos are but one example. In frequently-purchased products, such as deodorants, consumers consider only a small fraction of those available (typically 10%, Hauser and Wernerfelt 1990). Leverage can be huge. There are 350+ auto/truck brands on the market, but the typical consumer considers roughly 5-6 brands. A strategy that increases the likelihood that an automobile brand is considered could increase a firm's odds of making a sale from 1 in 350 to 1 in 6 – a substantial improvement.

Much of the conjoint-analysis literature and most conjoint-analysis applications have focused on preference or choice. Recently, a number of papers have focused on choice, conditioned on consideration, providing evidence that two-stage, consider-then-choose models often improve both realism and accuracy.¹ Sometimes these papers measure consideration explicitly; other times consideration is an inferred construct.

More recently, papers have begun to focus on the consideration decision itself recognizing that managerial actions can be taken to affect consideration directly. For example, advertising might stress a J. D. Power result, make salient a screening feature, or select product features that are likely to lead to consideration.

Research in consumer behavior suggests that the consideration decision might be fundamentally different than the choice decision (e.g., Bronnenberg and Vanhonacker 1996; DeSarbo et al., 1996; Hauser and Wernerfelt 1990; Jedidi, Kohli and DeSarbo, 1996; Mehta, Rajiv, and Srinivasan, 2003; Montgomery and Svenson 1976; Payne 1976; Roberts and Lattin, 1991, 1997; Shocker et al., 1991; Wu and Rangaswamy 2003). Consumers often process a large number of products (possibly hundreds) or a large number of features (possibly 50 or more) and make decisions rapidly, sometimes in seconds (Payne, Bettman and Johnson 1988, 1993). In many, but not all, cases, consumers use heuristic rules to screen products for future consideration. These rules are often simpler than those implied by the traditional additive-partworth rules used in conjoint analysis. Consumers might rank features and choose accordingly (lexicographic), focus on a few features to accept or eliminate alternatives (conjunctive, disjunctive, disjunctions of conjunctions), or use mixed rules (conjunctive to eliminate most alternatives, then compensatory for the remaining). Such rules can be “rational” because they balance cognitive or search efforts with the utility of choosing from the consideration set. They might also be ecologically rational because consumers can rely on market regularities and ignore certain features. Cars with large engines tend to be fast, have low mpg, and have sporty suspensions. In general, we expect consideration heuristics to be cognitively simpler than compensatory choice rules (e.g., Bettman, Luce and Payne 1998; Bröder 2000; Chakravarti and Janiszewski 2003; Chase, Hertwig and Gigerenzer 1998; Gigerenzer and Goldstein 1996; Gigerenzer and Todd 1999; Hogarth and Karelaia 2005; Kahneman and Tversky 1996; Johnson and Payne 1985; Murray and Häubl 2006; Newell, Weston and Shanks 2002, 2003; Payne, Johnson and Bettman 1988, 1993; Martignon and Hoffrage 2002; Martignon and Schmitt 1999; Schmitt and Martignon 2006; Simon 1955; Shugan 1980).

In this paper we review and contrast recent research on non-compensatory (and compensatory) consideration decisions. These papers propose a variety of “revealed” and “self-explicated” methods that attempt to infer potentially non-compensatory decision rules that consumers use to form consideration sets. Some methods measure consideration directly; others infer consideration as a latent construct. In some cases data are collected via on-line questionnaire; in other cases not. Some use incentive-compatible measures; others not. In some cases, non-compensatory models perform better; in some cases we cannot reject compensatory models. And, the product categories vary: some are more complex than others.

¹ Papers using two- (or more) stage models include: Andrews and Manrai 1998; Andrews and Srinivasan 1995; Desai and Hoyer 2000; Desarbo and Jedidi 1995; Ding, et al. 2009; Erdem and Swait 2004; Gensch 1987; Gensch and Soofi 1995a, 1995b; Gilbride and Allenby 2004; 2006; Häubl and Trifts 2000; Hauser, et al. 2009; Jedidi, Kohli and DeSarbo 1996; Jedidi and Kohli 2005; Kamis 2006; Kardes, et al. 1993; Lapersonne, Laurent and Le Goff 1995; Moe 2006; Nedungadi 1990; Newman and Staelin 1972; Oppewal, Louviere and Timmermans 1994; Posavac, et al. 2001; Punj and Staelin 1983; Roberts and Lattin 1997; Shocker, et al. 1991; Siddarth, Bucklin and Morrison 1995; Swait 2001; Swait and Ben-Akiva 1987; Urban, Hauser and Roberts 1990; and Yee, et al. 2007.

Through this comparison we posit empirical generalizations suggesting differences among data collection procedures, estimation methods, underlying theoretical models and, most importantly, which are most appropriate for which product-category characteristics.

THE CONSIDERATION SET

In the early 1970s most new products were tested in expensive test markets often costing between one and two million dollars. In response, many researchers developed laboratory test markets based on simulated stores and choice models (e.g., Silk and Urban 1978). Researchers quickly discovered that the average consumer did not consider all brands on the market. For example, if there were 32 deodorants on the market, the average consumer considered only 4 brands. More importantly, accurate forecasts of market share or volume required that choice models be conditioned on the consideration set, with separate models to indicate how a new product would enter the consideration set. The laboratory test markets modeled a consumer's consideration set explicitly and, in doing so, allowed managers to evaluate advertising and distribution spending designed to enable the new product to be considered.

Since the 1970s, the consideration-set phenomenon has been well-documented (e.g., Jedidi, Kohli and DeSarbo, 1996; Montgomery and Svenson 1976; Paulssen and Bagozzi 2005; Payne 1976; Roberts and Lattin, 1991; Shocker et al., 1991). The phenomenon has an economic rationale (Hauser and Wernerfelt 1990). The basic idea is that value of a consideration set is based on the "utility" that a consumer receives by choosing a set's maximum element minus the cost of searching for the maximum element. If a new item is to be considered then the expected value of choosing from the expanded set (now $n + 1$ products) minus the expected value of choosing from n products must exceed the cost of searching over $n + 1$ rather than n products. Managers can increase the perceived value of the $n + 1^{\text{st}}$ product with new product features or advertising or decrease the search cost with communication, sampling, or promotion. Of course, competitors will, in turn, enhance their brands in the same way as they defend their brands (Hauser and Shugan 1983).

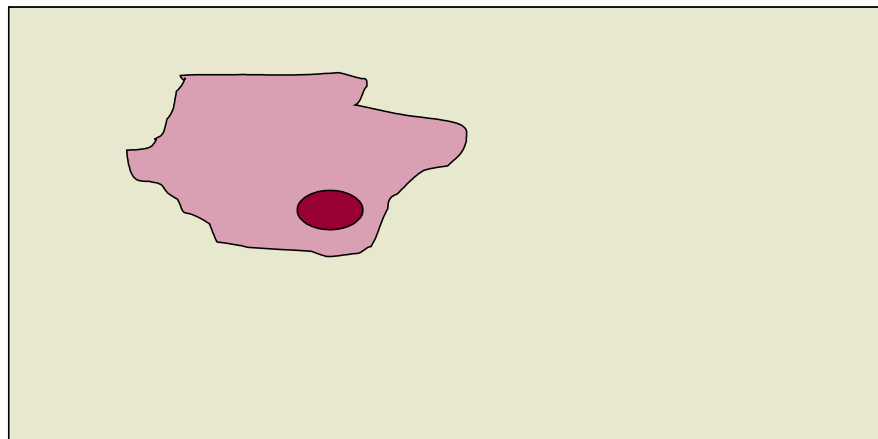
Fortunately, consideration decisions can be measured directly. Much as a researcher might ask respondents to choose among profiles in a choice-based conjoint-analysis exercise, modified formats enable researchers to ask respondents which profiles they would consider. See Figure 1. In this particular format a profile is highlighted in a center box as respondents run their mouse over a "bullpen" of profiles. Respondents then indicate whether or not they would consider the profile. Considered profiles are displayed on the right and respondents can add or delete profiles until they are satisfied with their consideration sets. Such formats are easy to program and respondents find them easy to use.

Figure 1
 “Bullpen” Measures of Consideration



Such formats beg the question: does it help to measure and model consideration decisions? For example, if the focus is on ultimate choice, why not simply model the decision to choose a profile from the set of all profiles, rather than model the decision in two steps? As illustrated in Figure 2, we can write equivalently that $\text{Prob}(\text{choose } a) = \text{Prob}(\text{choose } a \text{ from consideration set } C) * \text{Prob}(\text{consider set } C)$. The motivation for modeling consideration lies in research that indicates that consumers often use different (heuristic) decision rules for consideration than for choice. (In addition, as argued above, managers can affect consideration directly.)

Figure 2
 Conceptual Representation of Choice within a Consideration Set*



*The red circle is the chosen profile, the shaded irregular region is the consideration set, and the grey area is the full choice set.

DECISION-RULE HEURISTICS IN CONSIDERATION SET DECISIONS

Heuristics are common in consideration-set decisions. For example, examine Figure 3. In this figure respondents are asked to choose one GPS from among 32 candidate GPS profiles that vary on 16 features. Most respondents would be unlikely to examine all features of all GPSs and form an additive-partworth compensatory evaluation. Rather, a respondent might focus on a relatively few features (color display, long battery life, etc.) and eliminate those that do not have the desired features (a “conjunctive” decision rule). Or, the respondent might use another simplifying heuristic. Research suggests that this task is not unlike tasks faced by real consumers in real market environments.

Figure 3
Choosing Among 32 GPS Profiles That Vary on 16 Features



We elaborate various heuristic rules in a later section, but one aspect shared by all of these rules is cognitive simplicity. Cognitive simplicity is based on experimental evidence in a variety of contexts (as early as 1976 by Payne; reviews by Payne, Bettman and Johnson 1988, 1993). Related evidence suggests that cognitively simple “fast and frugal” decision rules are prescriptively good ways to make decisions (Brandstatter et al. 2006; Dawkins 1998; Einhorn and Hogarth 1981; Gigerenzer and Goldstein 1996; Gigerenzer, Hoffrage and Kleinbolting 1991; Gigerenzer and Todd 1999; Hogarth and Karelaia 2005; Hutchinson and Gigerenzer 2005; Martignon and Hoffrage 2002; Simon 1955; Shugan 1980). Basically, with a reasonable consideration set (say 5-6 automobiles), the best choice from the consideration set is close in utility to the best choice from 350 automobiles, but the savings in evaluation costs are huge (Internet search, dealer visits, test drives, reading *Consumer Reports*, talking to friends, etc.). Furthermore, cognitively simple decision rules are often robust with respect to errors in evaluation.

Cognitively simple decision rules work well in typical “real world” choice environments because in such environments features tend to be correlated. Automobiles with large engines

tend to have good leg room, good trunk room, seat five comfortably, and are often luxurious. However, such automobiles also get lower gas mileage and are expensive. Market offerings tend to evolve jointly with consumer heuristics. If heuristics worked well in past decisions, consumers tend to continue to use the heuristics. If consumers use heuristics, firms react with their product offerings which, in turn, further justify consumer heuristics. Heuristics might even diffuse through word of mouth. While it is possible to show violations when heuristics lead to absurd outcomes, such extreme situations are less common in everyday decisions.

In one illustration a recent MIT study asked respondents to sort the profiles into “definitely would consider,” “definitely would not consider,” or “not sure.” (More detail in Hauser, et al. 2009.) Respondents first sorted quietly 50 profiles, then made verbal comments as they sorted the remaining 50 profiles. When they finished sorting, respondents re-examined the card stacks and articulated decision rules. All sorting was videotaped with a camera on the cards and a camera on the respondent. Afterwards, independent judges evaluated the consumers’ decision rules (with high reliability using procedures recommended by Hughes and Garrett 1990; Perreault and Leigh 1989). The results were informative. Most respondents (87%) took less than 8 seconds per vehicle and most respondents (76%) used a cognitively-simple decision rule.

HEURISTICS ARE MORE LIKELY IN SOME CONTEXTS THAN OTHERS

Heuristics are important, but not necessarily in every managerial context. For complex technical business-to-business products, such as a high speed printer, in which there are relatively few alternatives, we might expect a buying center to evaluate all alternatives using a full-information compensatory decision process. On the other hand, in a category such as GPSs in which there are many alternatives, many features, and much information available (on the Internet) from a variety of sources, we might expect consumers to use a cognitively-simple screening heuristic to balance search/evaluation cost with the value of a higher-value “best” product.

Fortunately, the behavioral literature suggests characteristics of decision environments where heuristics are more likely (Bettman, Luce and Payne 1998; Bettman and Park 1980b; Bettman and Zins 1977; Chakravarti, Janiszewski and Ülkumen 2009; Chernev 2005; Frederick 2002; Kardes, et al. 2002; Levin and Jasper 1995; Lussier and Olshavsky 1997; Luce, Payne and Bettman 1999; Payne, Bettman and Johnson 1988; 1993; Payne, Bettman and Luce 1996; Punj and Brookes 2002; Ratneshwar, Pechmann and Shocker 1996; and Steckel, et al. 2005; among others). Heuristic decision rules are more likely when:

- there are more products

- there are more features to be evaluated

- quantifiable features are more salient

- there is more time pressure

- the consumer is in an early phase of his/her decision process (heuristics are dynamic; they change as the consumer goes through phases of his/her decision process)

- the effort required to make a decision is more salient

- the reference class is well-defined (e.g., mature products)

consumers are more familiar with the category (and have constructed well-defined decision rules)

consumers have cognitive styles focused on task completion

Decision context influences decision rules. Context affects both survey design and projections to decision environments. For example, the following context effects influence the use of and type of decision heuristics.

response mode – choice tasks (as in CBC), rating tasks (as in ACA), matching, or bidding (for example, respondents are more lexicographic in choice than matching)

familiarity with the product category – preferences are more robust among experienced consumers and, hence, less dependent on response mode

choice set composition – influences such as asymmetric dominance, compromise effects, and other contexts encourage heuristic decision rules

negative correlation among features in the choice set – when environments are more regular (e.g., “efficient frontier”), the cost of “mistakes” is less and heuristics perform better (Johnson and Meyer 1984). However, if the choice set is small, negative correlation induces utility balance which makes the decision more difficult, thus leading to more compensatory rules.

We illustrate these insights with two decision contexts: automobiles and web-based purchasing. Automobiles have a large number of features and a large number of brands (and variations within brands). The effort to search for the information is extensive (e.g., dealership experience, WOM, in addition to product features), and the decision is complex. Most automobile purchasing happens over a period of months, so there is an early phase in which brands are eliminated. This is particularly true because many alternatives (SUV, light truck, van, sporty coupe, cross-over) are difficult to compare. All of these characteristics imply heuristic processes are likely in the early phases of a consumer’s automobile decision.

Many web-based buying situations include many alternatives. For example, in March 2009 there were 181 flat-panel televisions available at bestbuy.com. Figure 4 illustrates just a portion of a page listing the large number of mobile telephones available at various web sources. Both mobile telephones and flat-panel televisions have many features and specifications. Without filtering, consumers easily face information overload and an overwhelming choice decision. Filtering based on price, screen size, brand, etc. makes heuristics even less cognitively taxing. All of these characteristics lead to greater heuristic processing. However, web-based buying also reduces time pressure and search cost, mitigating some of the tendency to favor heuristic processing.

Figure 4
Illustrative Web Page for Mobile Telephones



Not all decisions encourage heuristics. The following decision characteristics make heuristics less likely:

- simple choice sets with few alternatives
- few features or levels
- really new products with really new features
- low time pressure and search costs
- final decisions after initial heuristic screening

DECISION-RULE HEURISTICS STUDIED IN THE LITERATURE

There is a rich set of heuristics identified and studied in the 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 Czaczkcs 1995; Gilbride and Allenby 2004, 2006; Hauser 1986; Hauser et al. 2009; 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 1986; Mela and Lehmann 1995; Moe 2006; Montgomery and Svenson 1976; Nakamura 2002; Payne 1976; Payne, Bettman, and Johnson 1988; Punj 2001; Shao 2006;

Svenson 1979; Swait 2001; Tversky 1969, 1972; Tversky and Sattath 1987; Tversky and Simonson 1993; Vroomen, Franses and van Nierop 2004; Wright and Barbour 1977; Wu and Rangaswamy 2003; Yee et al. 2007). We illustrate the most commonly-studied heuristics with examples drawn from a hypothetical evaluation of automobiles. The heuristics are disjunctive, conjunctive, subset conjunctive, lexicographic, elimination-by-aspects, and disjunctions of conjunctions.

Disjunctive. In a disjunctive rule a profile is considered if one feature or set of features is above a threshold. For example, a consumer might consider all hybrid sedans or all sporty sedans. Hybrids would be considered even if they were not sporty and sporty sedans would be considered even if they were not hybrids. In a disjunctive rule, the other features do not matter.

Conjunctive. In a conjunctive rule a profile must have all of its features above minimum levels. Of course, some minimum levels can be such that all profiles satisfy them, e.g., at least 5 miles per gallon. For example, a consumer might set minimum levels for fuel economy, crash test ratings, quality ratings, leg room, acceleration, ride & handling, safety, audio systems, navigation systems, warranty, price, etc. Technically, minimum levels must be set for all features, even if the minimum levels are so low that all profiles pass.

Subset conjunctive. In a subset conjunctive rule a profile must have S features above a threshold. Subset conjunctive generalizes both disjunctive ($S = 1$) and conjunctive ($S = \text{number of features}$). As defined and applied, any S of the features need to be above the threshold. For example, if the consumer had already limited his/her search to profiles that vary only on fuel economy, quality ratings, and ride & handling, then a subset conjunctive model ($S = 2$) would imply that a vehicle is considered if either (fuel economy and quality) or (fuel economy and ride & handling) or (quality and ride & handling) were above minimum thresholds.

Disjunctions of conjunctions (DOC). In a DOC rule a profile will be considered if one or more conjunctions is satisfied. DOC thus generalizes disjunctive, conjunctive, and subset conjunctive models. For example, a consumer might consider a sedan if it is a hybrid that seats five passengers or a sporty sedan that has great ride & handling. The sporty sedan need not be a hybrid and the hybrid need not have great ride & handling. In the MIT/GM study cited respondents described DOC models when they articulated their decision processes.

Lexicographic. In a lexicographic rule the consumer first ranks the features. He/she then ranks the profiles using successively the first-ranked feature, breaking ties with the second-ranked feature, breaking ties further with the third-ranked features, etc. For example, a consumer might rank all hybrids over other fuel classes. Within hybrids, he/she might next rank vehicles on crash test ratings, then on quality ratings, then on ride & handling, etc. Lexicographic rules are usually defined for choice providing a ranking (allowing ties) of all profiles in the choice set. When applied to the consideration decision, we must also define a cutoff which can either be a limit on the number of profiles or on the depth of ranking of the features used in the rule. With the latter, if we only observe the consideration set and not the ranking within the consideration set, a lexicographic rule is indistinguishable from a conjunctive rule.

Elimination-by-Aspects (EBA). In a (deterministic) EBA rule the consumer successively chooses aspects (feature levels) and eliminates all profiles that have that aspect. Because an aspect is binary, a profile either has it or not, we can define aspects by their negation to produce an equivalent rule of acceptance-by-aspects (ABA). For example, in EBA a consumer might first

eliminate all conventional gasoline/diesel powered vehicles. (Alternatively, accept all hybrids.) The consumer might next eliminate all vehicles with crash test ratings below 3 stars, etc. Like lexicographic rules, EBA provides a ranking (with potential ties) of all profiles and, like lexicographic rules, EBA is indistinguishable from a conjunctive rule if we just observe the consideration set. EBA was originally defined by Tversky (1972) as a probabilistic rule in which the consumer chooses aspects with probability proportional to their measures. However, many researchers have interpreted that probability as the analyst's uncertainty and have assumed that the consumer eliminates aspects in a fixed order (Johnson, Meyer and Ghose 1989; Montgomery and Svenson 1976; Payne, Bettman and Johnson 1988; and Thorngate 1980).

Additive partworth rule (and q -compensatory rules). We normally think of an additive partworth model as a compensatory model, that is, high levels on some features can compensate for low levels on other features. However, if the partworths are extreme, an additive partworth rule can act like a non-compensatory rule. For example, if there are F binary features and if partworths are in the ratios of $2^{F-1}, 2^{F-2}, \dots, 2, 1$, then no combination of lower-ranked features can compensate for a low level on a higher-ranked feature. In this case, the additive partworth model acts as if it were lexicographic. Other non-compensatory rules also have additive representations (Jedidi and Kohli 2005; Kohli and Jedidi 2007; Meyer and Johnson 1995; Olshavsky and Acito 1980). Thus, an additive-partworth rule is, in fact, a mixed compensatory/non-compensatory rule. To address this issue some researchers define a q -compensatory rule as an additive-partworth rule in which the ratio of any two feature importances (max – min partworths for a feature) is no more than q (Bröder 2000; Hogarth and Karelaia 2005; Martignon and Hoffrage 2002; Yee, et al. 2007). With small q (typically $q = 4$), q -compensatory rules and non-compensatory rules form disjoint sets.

RELEVANCE TO MANAGERS

Non-compensatory decision rules, whether applied to choice or consideration, have received considerable academic attention. But do they have practical managerial relevance? We know of no general study to indicate when they do and when they do not have managerial relevance. For example, it is entirely possible that a heterogeneous mix of conjunctive screening rules could be approximated well by an additive-partworth model (e.g., Abe 1999; Andrews, Ainslie and Currim 2008; Dawes 1979; Dawes and Corrigan 1974; Meyer and Johnson 1995). This is particularly true because, as cited earlier, many non-compensatory rules can be represented by additive-partworth models. While we await more systematic research, we provide two published anecdotes from Hauser, et al. (2009).

Hauser, et al. studied consideration decisions for handheld GPSs. There were two brands in their study: Magellan and Garmin. On average the Magellan brand had higher partworths, thus in any additive-partworth market simulator a switch from Garmin to Magellan would improve market share. However, when non-compensatory models were estimated, the researchers found that 12% of the respondents screened on brand and, of those, 82% preferred Garmin. For the other 88% (100% – 12%), brand had no impact on consideration. If this model was correct (and it did predict a holdout task better), then a switch from Garmin to Magellan would reduce market share – exactly the opposite of that predicted by an additive-partworth model.

In the same study, “extra bright display” for a handheld GPS was the most important feature based on additive partworths. A market simulator predicted that adding an extra bright display for an addition \$50 would increase share by 11%. However, DOC rules suggested that those

respondents who screened for extra bright displays also tended to screen against higher price. A DOC-based simulator predicted only a 2% increase in share.

GENERAL APPROACHES TO UNCOVER HEURISTICS

Researchers have addressed consideration sets and non-compensatory decision rules with a myriad of approaches. There are many potential taxonomies; we feel the following taxonomy captures the essence of the approaches:

consideration and decision rules revealed as latent constructs

consideration measured directly and decision rules revealed by the ability of the rules to fit the survey measures

decision rules measured directly through self-explicated questions.

We discuss each in turn.

CONSIDERATION AND DECISION RULES AS LATENT CONSTRUCTS

In these approaches the researcher observes only choices and the feature-levels of the profiles in the choice set. The researcher postulates a two-stage consider-then-choose decision process and postulates basic decision rules for each stage. The parameters of the model, for example minimum feature levels in the first stage and partworths in the second stage, are then inferred by either Bayesian or maximum-likelihood methods. We illustrate this approach with three perspectives: Bayesian, choice-set explosion, and soft constraints.

Bayesian. Gilbride and Allenby (2004; 2006) use a Bayesian approach. In their 2004 paper they establish either conjunctive, disjunctive, or linear screening rules for the consideration stage and a compensatory (probit-like) decision rules for choice from the consideration set. Consideration is not measured, but rather modeled with data augmentation; both the first and second stages of the decision process are inferred simultaneously. Because the first stage is streamlined, their model scales well in a camera application with 6 profiles (plus a none option), seven features, and a total of 23 levels. They find that 92% of their respondents are likely to have used a non-compensatory first-stage screening rule even though the number of alternatives and features was relatively modest.

Choice-set Explosion. Andrews and Srinivasan (1995), Chiang, Chib and Narasimhan (1999), Erdem and Swait (2004), Swait and Ben-Akiva (1987) and others use choice-set explosion and maximum-likelihood methods. These researchers assume that the consideration decision is made with a logit-like compensatory decision rule enabling the researcher to model the probability of consideration for all $2^n - 1$ consideration sets, where n is the number of profiles in the choice set. They then assume a second-stage logit for choice from within the consideration set. They reduce the dimensionality with assumptions of independence, but the models still have complexity that is exponential in n . If n gets too large the curse of dimensionality makes the model too onerous to estimate. For appropriate-sized problems the choice-set-explosion models enable researchers to explore the drivers of consideration and enable researchers to relate these drivers to characteristics of the consumers and/or choice environment.

Soft constraints. Recognizing the curse of dimensionality, Swait (2001) proposes a two-stage-like model with conjunctive and disjunctive cutoffs. The key idea is that these constraints come directly from respondents' self-statements and are treated as "soft" in the sense that they influence cutoffs but are not necessarily binding. Swait claims superior predictive ability relative to choice-set explosion based on an "extremely powerful" increase in the log-likelihood values. Swait also points out that the model itself is estimated simultaneously and, thus, does not assume an ordering of the two stages of cutoffs and additive partworths.

CONSIDERATION MEASURED, DECISION RULES INFERRED

Since the early 1970s researchers have measured consideration sets directly. Respondents find the task intuitive and such measures significantly enhance new product forecasts (Brown and Wildt 1992; Hauser 1978; Silk and Urban 1978; Urban and Katz 1983). Figure 1 provides one example. For a variety of web-based formats see also Ding, et al. (2009), Gaskin, et al. (2007), Hauser, et al. (2009), and Yee, et al. (2007). Direct measurement presents three challenges. First, if we believe the evaluation-cost theory of consideration sets, then consumers form consideration sets by making tradeoffs between the increased utility from larger sets and the increased search cost for larger sets. *In vivo* search cost is set by the marketplace environment, but *in vitro* it is set by the measurement instrument. For example, Hauser et al. (2009) test four web-based formats that vary *in vitro* search cost. They find that respondents choose smaller consideration sets when respondents are asked to indicate only considered profiles versus when they are asked to indicate only rejected profiles. The size of the consideration set when respondents need evaluate all profiles is in-between. Fortunately, the choice rules do not seem to vary that dramatically; the process of choice can still be measured with some fidelity. The second challenge is that context matters (see references cited in a previous section). The size of the evaluation set, the number of features, how decisions are framed, whether there is negative correlation among features, whether some profiles are dominated asymmetrically, and other context effects can all influence decision rules, rules that might be constructed on the fly. The third challenge is when incentive alignment is coupled with consideration-set measurement. Consideration is an intermediate construct, not the final choice. Incentives must be sufficiently vague, yet effective, so that the respondent believes that he/she should specify a consideration set that applies *in vivo*. See examples in Ding et al. (2009) and Kugelberg (2004). The important caveat for all three challenges is that researchers must pay attention to context and work to ensure that the *in vitro* measurements approximate *in vivo* projections.

Once consideration is measured *in vitro*, there are a variety of methods to estimate the decision rules that best explain the consideration decisions observed on calibration tasks. There are two basic estimation strategies: Bayesian with simpler structure and machine-learning pattern-matching algorithms. For example, the Gilbride-Allenby (2004) approach is easily modified for explicitly measure consideration. Bayesian methods can easily be written for subset conjunctive, *q*-compensatory (rejection sampling), and, of course, additive partworth models. Machine-learning algorithms use either math programming or logical analysis of data (LAD, Boros, et al. 1997; 2000).

There are at least two issues to be addressed when using revealed estimation for consideration-set rules. First is the curse of dimensionality. Non-compensatory models can easily over fit data. For example, there are $3^{23} = 94,143,178,827$ potential DOC rules with 23

binary features. With such large numbers it is not feasible to have prior or posterior probabilities for each decision rule. Rather, researchers must simplify the model as in Gilbride or Allenby (2004) or impose constraints that the decision rules are cognitively simple as in Hauser et al. (2009). The second issue is the robustness of the additive-partworth model. An additive-partworth model is likely to fit the data well, even if the process is non-compensatory. To address this issue, researchers often estimate a q -compensatory model and compare it to a non-compensatory model. This two-step evaluation provides insight because the additive-partworth model can nest both.

We are aware of only one comprehensive comparison of the predictive ability of revealed-decision-rule estimation on directly-measured consideration. Hauser, et al. (2009) compare five Bayesian models (conjunctive, disjunctive, subset conjunctive, q -compensatory, additive partworth) and seven pattern-recognition models (conjunctive, disjunctive, subset conjunctive, q -compensatory, additive-partworth, DOC math program, DOC LAD) on the same data. The models were estimated when respondents were asked to evaluate an orthogonal design of 32 GPSs. Predictions were evaluated on a different set of 32 GPSs (after a memory-cleansing task). They found that:

the relative predictive ability of Bayesian vs. pattern-recognition methods depended upon the posited decision model

DOC models improved prediction significantly relative to conjunctive, disjunctive, or subset conjunctive for both Bayesian and pattern-recognition methods

there was no significant difference between the math programming and LAD DOC models

non-compensatory models did better than q -compensatory models, but

additive partworth models did almost as well as DOC models.

Their study is limited to a single category in an environment chosen to favor non-compensatory models. Abundant research opportunities will increase our knowledge with further testing.

DECISION RULES MEASURED DIRECTLY THROUGH SELF-EXPLICATED QUESTIONS

Directly-elicited non-compensatory measures have been used almost since the beginning of conjoint analysis. Casemap, Adaptive Conjoint Analysis (ACA), and other methods all include options to ask respondents to indicate unacceptable levels or products (Green, Krieger and Banal 1988; Malhotra 1986; Klein 1986; Srinivasan 1988; Srinivasan and Wyner 1988; Sawtooth 1996). However, these modules have met with mixed success; respondents happily choose profiles with unacceptable levels. More recently, researchers have experimented with improved formats. Swait (2001) uses self-explicated cutoffs as soft constraints. Adaptive Choice-Based Conjoint Analysis (ACBC) uses a multi-step procedure in which (1) respondents are asked to indicate a profile that they would consider, (2) a pool of profiles is created as perturbations on that profile, (3) respondents are shown screens of 3-5 profiles and asked for consideration, and (4) if a feature-level is always rejected or accepted a pop-up “avatar” (a graphic of an attractive interviewer can be included, though is not required) confirms the non-compensatory decision rule (Sawtooth Software 2008). Ding, et al. (2009) ask respondents to write an unstructured e-

mail to a friend who will act as their agent and purchase the product for them. Figure 5 provides an example e-mail from a Hong Kong respondent who was evaluating mobile telephones.

Figure 5
Example “E-Mail” Direct Elicitation

The screenshot shows a web-based survey interface. At the top left, the title "MobilePhone Study" is displayed in red. To the right, it says "Hi, Guest". Below the title, there is a blue header bar with "SURVEY (Part 2)" on the left and "Phone Features" on the right. The main content area is titled "Part 2" and contains the following text: "In the Teaching Agent to Buy task, you told us your instructions one at a time. Now we want you to tell us these instructions again in a different format -- please write them as if you are writing an email (that provides instructions) to a friend who is going to buy a mobilephone for you. In this format, it might be easier for the human agents to understand. Please start the email with 'Dear friend', and end it with your name. These inputs will later be emailed to the human agents if you were selected as a winner." Below this text is a text input field containing a sample email response: "Dear friend, I want to buy a mobile phone recently and I hope u can provide some advice to me. 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." At the bottom of the form is a button labeled "Next Step".

Directly-elicited decision-rule measures have become more accurate for a number of important reasons. Formats can now be incentive-aligned, that is, the respondent believes that he/she will receive a prize (in a lottery) and that the prize depends upon his/her answers to the questions (Ding 2007; Ding, Grewal and Liechty 2005; Park, Ding and Rao 2008). With incentive-aligned methods, truthful questions are dominant. If the incentives are sufficient, then the respondent is also encouraged to think hard about the answers. “Natural tasks” further enhance accuracy. In ACBC respondents evaluate profiles and then respond to an avatar. In Ding et al. respondents write e-mails that are similar to those that they would write to friends. Researchers are beginning to appreciate the value of “build your own (BYO)” profiles as in the first phase of ACBC. Typically, consumers consider but a small fraction of the available products, thus one gains significantly more information from knowing a profile is considered than from knowing a profile is not considered (Silinskaia and Hauser 2009). Finally, the wide use of voice-of-the-customer methods has led to a market-research workforce that is adept at quantifiable coding of qualitative data (Griffin and Hauser 1993; Hughes and Garrett 1990; Perreault and Leigh 1989).

Ding et al. (2009) compare directly-elicited decision rules to decision rules inferred from the analysis of directly-measured consideration (decomposition). The decompositional benchmarks are a q -compensatory logit model, an additive-partworth logit model, a lexicographic model estimated with Yee, et al.’s (2007) Greedoid dynamic program, and LAD. Respondents were asked to either evaluate profiles or state decision rules (calibration data). Predictions were based

on data collected three weeks later when respondents evaluated 32 profiles. The researchers found:

- direct elicitation predicts as well as decomposition (no significant difference)
- non-compensatory rules predict better than q -compensatory rules,
- additive partworths do as well as pure non-compensatory rules

While there is no improvement in predictive ability relative to decomposition, the directly-elicited rules have the advantage that they are less subject to the curse of dimensionality. They scale well to large problems. For example, Ding, et al. demonstrate that respondents can answer easily questions about a very complex category that would have required over 13 thousand profiles in an orthogonal design.

TAKE HOME LESSONS

No review of the literature is perfect and ours is not without its caveats. It is very difficult to compare across sub-literatures and it is not yet feasible to do a meta-analysis because the criteria with which researchers evaluate models varies widely. Among the measures we found were hit rates, log likelihood measures, Kullback-Leibler divergence, t -tests, ρ^2 (pseudo- R^2), and U^2 (percent of information explained). Some papers correct for the number of profiles (predicting choice from among 2 profiles is easier than from among 32 profiles), others do not and do not report the number of profiles. In consideration decisions null models are particularly strong. For example, if only 20% of the profiles are considered, then a null model which predicts that nothing is considered will predict all not-considered profiles correct – an 80% hit rate. Even a random model will predict 68% of the profiles correctly ($0.8^2 + 0.2^2$). In the papers we reviewed benchmarks varied considerably and the null models were not equally challenging. Predictive ability alone should not be used to distinguish models. Detailed information on the choice/consideration context was often omitted even though research suggests that context can have a considerable influence.

Nonetheless, we were able to identify empirical generalizations that appear to hold. These include:

- non-compensatory decision rules for consideration decisions are common in many categories (see Table 1 for some examples).
- non-compensatory decision rules often predict better than purely compensatory rules (e.g., q -compensatory rules), but
- the unconstrained additive-partworth model is robust and hard to beat on predictive measures.
- complex situations favor non-compensatory decision rules, but
- non-compensatory rules often predict well in even simple situations.
- there are many ways to measure and/or estimate non-compensatory decision rules but, to date, no single approach appears to dominate.

there are excellent (and intuitive) anecdotes that managers should pay attention to non-compensatory decision rules but, to date, there is no comprehensive theory as to when.

SUMMARY

Non-compensatory decision rules for consideration decisions are growing in relevance. Figure 6 provides the date of publication of the 132 articles we reviewed. This is not a random sample, but it does suggest a growing interest. Non-compensatory decision rules for consideration have a long history in marketing, but powerful computers, efficient algorithms, and new theory is providing exciting new measurement and estimation methods. This research is likely to have increasing impact as researchers push further the limits of scalability, develop easy-to-use software, and explore synergies with behavioral experiments.

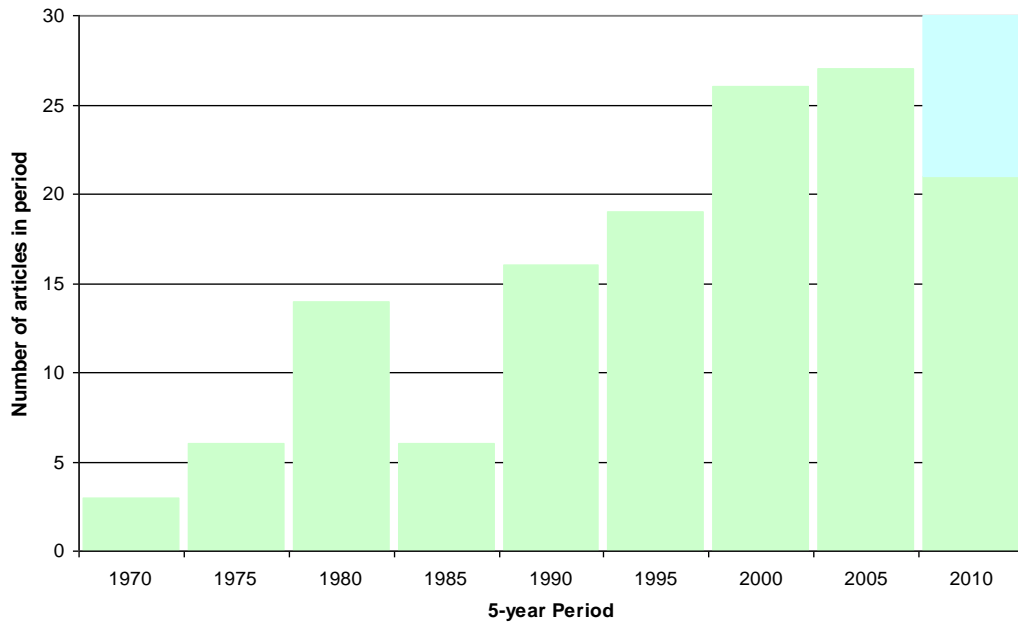
And there are many research opportunities. We need a theory (or generalization) of when and how models of non-compensatory decision rules for consideration influence managerial theories. We do not yet have practical models of the effect of such decision rules on market-structure equilibria. And we need many more predictive tests of current (and yet-to-be-developed) models. The future is indeed exciting and, we hope, fun.

Table 1
Example Predictive Ability of Non-Compensatory Models

PRODUCT CATEGORY	Percent non-compensatory	Fit Equal/ Better
Air conditioners (Shao 2006, protocol)	89% screen, 67% two-stage	
Automobiles (Hauser, et al. 2009, process tracing)	76% cognitively simple	
Automobiles (Levin, Jasper 1995, process tracing)	86% non-compensatory	
Batteries (Jedidi, Kohli 2005, subset conjunctive)		equal (a)*
Cameras (Gilbride, Allenby 2004, conj., disjunctive)	92% non-compensatory	better
Cell phones (Ding, et al., 2009 conj./compensatory)	78% mixed	better (q), equal (a)
Computers (Kohli, Jedidi, 2007, lexicographic)	2/3rds lexicographic	equal (a)
Computers (Jedidi, Kohli 2005, subset conjunctive)		"virtually identical"
Computers (Yee, et al. 2007, lexicographic)	58% lexicographic (17% tied)	better (q), equal (a)
Documentaries (Gilbride, Allenby 2006, screening)		better in-sample fit
GPSs (Hauser, et al. 2009, disjunctions of conj.)		better
MBA admissions (Elrod, et al. 2004, GNH)		better model selection
Rental cars (Swait 2001, soft cutoffs)		better in-sample fit
Smartphones (Yee, et al. 2007, lexicographic)	56% lexicographic	better (q), equal (a)
Supermarket product (Fader, McAlister 1990, EBA)		equal to logit

* a = relative to an additive-partworth model, q = relative to a q-compensatory model, conj. = conjunctive

Figure 6
 Dates of Non-Compensatory Articles
 (Projected through the end of 2010)



REFERENCES

- Abe, Makoto (1999), "A Generalized Additive Model for Discrete-Choice Data," *Journal of Business & Economic Statistics*, 17 (Summer), 271-84.
- Andrews, Rick L., Andrew Ainslie and Imran S. Currim (2008), "On the Recoverability of Choice Behaviors with Random Coefficients Choice Models in the Context of Limited Data and Unobserved Effects," *Management Science*, 54 (January), 83-99.
- and Ajay K. Manrai (1998), "Simulation Experiments in Choice Simplification: The Effects of Task and Context on Forecasting Performance," *Journal of Marketing Research*, 35 (May), 198-209.
- and T. C. Srinivasan (1995), "Studying Consideration Effects in Empirical Choice Models Using Scanner Panel Data," *Journal of Marketing Research*, 32 (February), 30-41.
- Bettman, James R., Mary Frances Luce, and John W. Payne (1998), "Constructive Consumer Choice Processes," *Journal of Consumer Research*, 25, 3 (December), 187-217.
- and L. W. Park (1980a), "Effects of Prior Knowledge and Experience and Phase of the Choice Process on Consumer Decision Processes: A Protocol Analysis," *Journal of Consumer Research*, 7 (December), 234-248.
- and ----- (1980b), "Implications of a Constructive View of Choice for Analysis of Protocol Data: A Coding Scheme for Elements of Choice Processes," (Journal Unknown), 148-153.
- and Michel A. Zins (1977), "Constructive Processes in Consumer Choice," *Journal of Consumer Research*, 4 (September), 75-85.

- Boros, Endre, Peter L. Hammer, Toshihide Ibaraki, and Alexander Kogan (1997), "Logical Analysis of Numerical Data," *Mathematical Programming*, 79:163--190, August 1997
- , -----, -----, -----, Eddy Mayoraz, and Ilya Muchnik (2000), "An Implementation of Logical Analysis of Data," *IEEE Transactions on Knowledge and Data Engineering*, 12(2), 292-306.
- Brandstaetter, Eduard, Gerd Gigerenzer and Ralph Hertwig (2006), "The Priority Heuristic: Making Choices Without Trade-Offs," *Psychological Review*, 113, 409-32.
- Bröder, Arndt (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.
- Bronnenberg, Bart J., and Wilfried R. Vanhonacker (1996), "Limited Choice Sets, Local Price Response, and Implied Measures of Price Competition," *Journal of Marketing Research*, 33 (May), 163-173.
- Brown, Juanita J. and Albert R. Wildt (1992), "Consideration Set Measurement," *Journal of the Academy of Marketing Science*, 20 (3), 235-263.
- Chakravarti, Amitav and Chris Janiszewski, (2003), "The Influence of Macro-Level Motives on Consideration Set Composition in Novel Purchase Situations," *Journal of Consumer Research*, 30 (September), 244-58.
- , ----- and Gülden Ülkümen (2009), "The Neglect of Prescreening Information," *Journal of Marketing Research* (forthcoming).
- Chase, Valerie M., Ralph Hertwig, and Gerd Gigerenzer (1998), "Visions of Rationality," *Trends in Cognitive Sciences*, 2, 6 (June), 206-214.
- Chernev, Alexander (2005), "Feature Complementarity and Assortment in Choice," *Journal of Consumer Research*, 31 (March), 748-59.
- Chiang, Jeongwen, Siddhartha Chib, and Chakravarthi Narasimhan (1999), "Markov Chain Monte Carlo and Models of Consideration Set and Parameter Heterogeneity," *Journal of Econometrics*, 89, 223-48.
- Chu, P.C. and Eric E. Spires (2003), "Perceptions of Accuracy and Effort of Decision Strategies," *Organizational Behavior and Human Decision Processes*, 91, 203-14.
- Dawes, R. M. (1979), "The Robust Beauty of Improper Linear Models in Decision Making," *American Psychologist*, 34, 571-582.
- and B. Corrigan (1974), "Linear Models in Decision Making," *Psychological Bulletin*, 81, 95-106.
- Desai, Kalpesh K. and Wayne D. Hoyer (2000), "Descriptive Characteristics of Memory-Based Consideration Sets: Influence of Usage Occasion Frequency and Usage Location Familiarity," *Journal of Consumer Research*, 27 (December), 309-323.
- Desarbo, Wayne S. and Kamel Jedidi (1995), "The Spatial Representation of Heterogeneous Consideration Sets," *Marketing Science*, 14, 326-342.

- , Donald R. Lehmann, Greg Carpenter, and I. Sinha (1996), "A Stochastic Multidimensional Unfolding Approach for Representing Phased Decision Outcomes," *Psychometrika*, 61 (September), 485-508.
- Dawkins, Richard (1998), *Unweaving the Rainbow: Science, Delusion, and the Appetite for Wonder*, (Boston, MA: Houghton Mifflin Company).
- Ding, Min (2007), "An Incentive-Aligned Mechanism for Conjoint Analysis," *Journal of Marketing Research*, 54, (May), 214-223.
- , Rajdeep Grewal, and John Liechty (2005), "Incentive-Aligned Conjoint Analysis," *Journal of Marketing Research*, 42, (February), 67-82.
- , John R. Hauser, Songting Dong, Daria Silinskaia, Zhilin Yang, Chenting Su, and Steven Gaskin (2009), "Incentive-Aligned Direct Elicitation of Decision Rules: An Empirical Test," Working Paper.
- Einhorn, Hillel J. (1970), "The Use of Nonlinear, Noncompensatory Models in Decision Making," *Psychological Bulletin*, 73, 3, 221-230.
- (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, Hillel J., and Robin M. Hogarth (1981), "Behavioral Decision Theory: Processes of Judgment and Choice," *Annual Review of Psychology*, 32, 52-88.
- Elrod, Terry, Richard D. Johnson, and Joan White (2004), "A New Integrated Model Of Noncompensatory And Compensatory Decision Strategies," *Organizational Behavior and Human Decision Processes*, 95, 1-19.
- Erdem, Tülin and Joffre Swait (2004), "Brand Credibility, Brand Consideration, and Choice," *Journal of Consumer Research*, 31 (June), 191-98.
- Fader, Peter S. and Leigh 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.
- Fishburn, Peter C. (1974), "Lexicographic Orders, Utilities and Decision Rules: A Survey," *Management Science*, 20, 11 (Theory, July), 1442-1471.
- Frederick, Shane (2002), "Automated Choice Heuristics," in Thomas Gilovich, Dale Griffin, and Daniel Kahneman, eds., *Heuristics and Biases: The Psychology of Intuitive Judgment*, (Cambridge, UK: Cambridge University Press, chapter 30, 548-558.
- Ganzach, Yoav and Benjamin Czaczkes (1995), "On Detecting Nonlinear Noncompensatory Judgment Strategies: Comparison of Alternative Regression Models," *Organizational Behavior and Human Decision Processes*, 61 (February), 168-76.
- Gaskin, Steven, Theodoros Evgeniou, Daniel Bailiff, John 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 in Santa Rosa, CA, October 17-19, 2007.

- Gensch, Dennis H. (1987), "A Two-stage Disaggregate Attribute Choice Model," *Marketing Science*, 6 (Summer), 223-231.
- and Ehsan S. Soofi (1995a), "Information-Theoretic Estimation of Individual Consideration Sets," *International Journal of Research in Marketing*, 12 (May), 25-38.
- and ----- (1995b), "An Information-Theoretic Two-Stage, Two-Decision Rule, Choice Model," *European Journal of Operational Research*, 81, 271-80.
- Gigerenzer, Gerd and Daniel G. Goldstein (1996), "Reasoning the Fast and Frugal Way: Models of Bounded Rationality," *Psychological Review*, 103, 4, 650-669.
- , Ulrich Hoffrage, and H. Kleinbölting (1991), "Probabilistic Mental Models: A Brunswikian Theory of Confidence," *Psychological Review*, 98, 506-528.
- , Peter M. Todd, and the ABC Research Group (1999), *Simple Heuristics That Make Us Smart*, (Oxford, UK: Oxford University Press).
- Gilbride, Timothy and Greg M. Allenby (2004), "A Choice Model with Conjunctive, Disjunctive, and Compensatory Screening Rules," *Marketing Science*, 23, 3 (Summer), 391-406.
- and ----- (2006), "Estimating Heterogeneous EBA and Economic Screening Rule Choice Models," *Marketing Science*, 25 (September-October), 494-509.
- Green, Paul E., Abba M. Krieger, and Pradeep Bansal (1988), "Completely Unacceptable Levels in Conjoint Analysis: A Cautionary Note," *Journal of Marketing Research*, 25 (August), 293-300.
- Griffin, Abbie and John R. Hauser (1993), "The Voice of the Customer," *Marketing Science*, 12, 1, (Winter), 1-27.
- Haübl, Gerald and Valerie Trifts (2000), "Consumer Decision Making in Online Shopping Environments: The Effects of Interactive Decision Aids," *Marketing Science*, 19 (Winter), 4-21.
- Hauser, John R. (1978), "Testing the Accuracy, Usefulness and Significance of Probabilistic Models: An Information Theoretic Approach," *Operations Research*, Vol. 26, 3 (May-June), 406-421.
- (1986), "Agendas and Consumer Choice," *Journal of Marketing Research*, 23 (August), 199-212.
- and Steven M. Shugan (1983), "Defensive Marketing Strategy," *Marketing Science*, 2, 4, (Fall), 319-360.
- , Olivier Toubia, Theodoros Evgeniou, Rene Befurt and Daria Silinskaia (2009), "Cognitive Simplicity and Consideration Sets," forthcoming, *Journal of Marketing Research*.
- and Birger Wernerfelt (1990), "An Evaluation Cost Model of Consideration Sets," *Journal of Consumer Research*, 16 (March), 393-408.

- Hogarth, Robin M. and Natalia 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.
- Hughes, Marie Adele and Dennis E. Garrett (1990), "Intercoder Reliability Estimation Approaches in Marketing: A Generalizability Theory Framework for Quantitative Data," *Journal of Marketing Research*, 27, (May), 185-195.
- Hutchinson, John M. C. and Gerd Gigerenzer (2005), "Simple Heuristics and Rules of Thumb: Where Psychologists and Behavioural Biologists Might Meet," *Behavioural Processes*, 69, 97-124.
- Jedidi, Kamel, Rajiv Kohli, and Wayne S. DeSarbo (1996), "Consideration Sets in Conjoint Analysis," *Journal of Marketing Research*, 33 (August), 364-372.
- and ----- (2005), "Probabilistic Subset-Conjunctive Models for Heterogeneous Consumers," *Journal of Marketing Research*, 42 (November), 483-494.
- Johnson, Eric J. and Robert J. Meyer (1984), "Compensatory Choice Models of Noncompensatory Processes: The Effect of Varying Context," *Journal of Consumer Research*, 11 (June), 528-541.
- , -----, and Sanjoy Ghose (1989), "When Choice Models Fail: Compensatory Models in Negatively Correlated Environments," *Journal of Marketing Research*, 26 (August), 255-290.
- and John W. Payne (1985), "Effort and Accuracy in Choice," *Management Science*, 31, 395-414.
- Kahneman, Daniel and Amos Tversky (1996), "On the Reality of Cognitive Illusions," *Psychological Review*, 103, 3, 582-591.
- Kamis, Arnold (2006), "Search Strategies in Shopping Engines An Experimental Investigation," *International Journal of Electronic Commerce*, 11 (Fall), 63-84.
- Kardes, Frank, Gurumurthy Kalyanaram, Murali Chandrashekar, and Ronald J. Dornoff (1993), "Brand Retrieval, Consideration Set Composition, Consumer Choice, and the Pioneering Advantage," *Journal of Consumer Research*, 20 (June), 528-541.
- , David M. Sanbonmatsu, Maria L. Cronley, and David C. Houghton (2002), "Consideration Set Overvaluation: When Impossibly Favorable Ratings of a Set of Brands Are Observed," *Journal of Consumer Psychology*, 12, 4, 353-61.
- Klein, Noreen M. (1988), "Assessing Unacceptable Attribute Levels in Conjoint Analysis," *Advances in Consumer Research* vol. XIV, pp. 154-158.
- Kohli, Rajiv and Kamel Jedidi (2007), "Representation and Inference of Lexicographic Preference Models and Their Variants," *Marketing Science*, 26 (May-June), 380-99.
- Kugelberg, Ellen (2004), "Information Scoring and Conjoint Analysis," Department of Industrial Economics and Management, Royal Institute of Technology, Stockholm, Sweden.

- Lapersonne, Eric, Giles Laurent and Jean-Jacques Le Goff (1995), "Consideration Sets Of Size One: An Empirical Investigation Of Automobile Purchases," *International Journal of Research in Marketing*, 12, 55-66.
- Leven, Samuel J. and Daniel S. Levine (1996), "Multiattribute Decision Making in Context: A Dynamic Neural Network Methodology," *Cognitive Science*, 20, 271-299.
- Levin, Irwin P. and J. D. Jasper (1995), "Phased Narrowing: A New Process Tracing Method for Decision Making," *Organizational Behavior and Human Decision Processes*, 64 (October), 1-8.
- Lohse, Gerald J. and Eric J. Johnson (1996), "A Comparison of Two Process Tracing Methods for Choice Tasks," *Organizational Behavior and Human Decision Processes*, 68 (October), 28-43.
- Luce, Mary Frances, John W. Payne, and James R. Bettman (1999), "Emotional Trade-off Difficulty and Choice," *Journal of Marketing Research*, 36, 143-159.
- Lussier, Denis A. and Richard W. Olshavsky (1997), "Task Complexity and Contingent Processing in Brand Choice," *Journal of Consumer Research*, 6 (September), 154-65.
- Malhotra, Naresh (1986), "An Approach to the Measurement of Consumer Preferences Using Limited Information," *Journal of Marketing Research*, 23 (February), 33-40.
- Martignon, Laura and Ulrich Hoffrage (2002), "Fast, Frugal, and Fit: Simple Heuristics for Paired Comparisons," *Theory and Decision*, 52, 29-71.
- and Michael Schmitt (1999), "Simplicity and Robustness of Fast and Frugal Heuristics," *Minds and Machines*, 9, 565-93.
- Mehta, Nitin, Surendra Rajiv, and Kannan Srinivasan (2003), "Price Uncertainty and Consumer Search: A Structural Model of Consideration Set Formation," *Marketing Science*, 22(1), 58-84.
- Mela, Carl F. and Donald 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.
- Meyer, Robert and Eric J. Johnson (1995), "Empirical Generalizations in the Modeling of Consumer Choice," *Marketing Science*, 14, 3, Part 2 of 2, G180-G189.
- Moe, Wendy 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.
- Murray, Kyle B. and Gerald Häubl (2006), "Explaining Cognitive Lock-In: The Role of Skill-Based Habits of Use in Consumer Choice," manuscript, (January 23).
- Nakamura, Yutaka (2002), "Lexicographic Quasilinear Utility," *Journal of Mathematical Economics*, 37, 157-178.

- Nedungadi, Prakash (1990), "Recall and Consideration Sets: Influencing Choice without Altering Brand Evaluations," *Journal of Consumer Research*, 17 (December), 263-276.
- Newell, Ben R., Nicola J. Weston, and David R. Shanks (2002), "Empirical Tests Of A Fast-And-Frugal Heuristic: Not Everyone 'Takes-The-Best,'" *Organizational Behavior and Human Decision Processes*, 91, 82-96.
- and David R. Shanks (2003), "Take the Best or Look at the Rest? Factors Influencing 'One-Reason' Decision Making," *Journal of Experimental Psychology: Learning, Memory and Cognition*, 29, 1, 53-65.
- Newman, Joseph W. and Richard Staelin (1972), "Prepurchase Information Seeking for New Cars and Major Household Appliances," *Journal of Marketing Research*, 9 (August), 249-57.
- Olshavsky, Richard W. and Franklin Acito (1980), "An Information Processing Probe into Conjoint Analysis," *Decision Sciences*, 11, (July), 451-470.
- Oppewal, Harmen, Jordan J. Louviere, and Harry J. P. Timmermans (1994), "Modeling Hierarchical Conjoint Processes with Integrated Choice Experiments," *Journal of Marketing Research*, 31 (February), 92-105.
- Park, Young-Hoon, Min Ding and Vithala R. Rao (2008), "Eliciting Preference for Complex Products: A Web-Based Upgrading Method," *Journal of Marketing Research*, 45 (October), 562-574.
- Paulssen, Marcel and Richard P. Bagozzi (2005), "A Self-Regulatory Model of Consideration Set Formation," *Psychology & Marketing*, 22 (October), 785-812.
- Payne, John W. (1976), "Task Complexity and Contingent Processing in Decision Making: An Information Search," *Organizational Behavior and Human Performance*, 16, 366-387.
- , James R. Bettman, and Eric J. Johnson (1988), "Adaptive Strategy Selection in Decision Making," *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 14, 534-552.
- , -----, and ----- (1993), *The Adaptive Decision Maker*, (Cambridge, UK: Cambridge University Press).
- , -----, and Mary Frances Luce (1996), "When Time is Money: Decision Behavior Under Opportunity-Cost Time Pressure," *Organizational Behavior and Human Decision Processes*, 66 (May), 131-152.
- Perreault, William D., Jr. and Laurence E. Leigh (1989), "Reliability of Nominal Data Based on Qualitative Judgments," *Journal of Marketing Research*, 26, (May), 135-148.
- Posavac, Steven S., David M. Sanbonmatsu, Maria L. Cronley, and Frank R. Kardes (2001), "The Effects of Strengthening Category-Brand Associations on Consideration Set Composition and Purchase Intent in Memory-Based Choice," *Advances in Consumer Research*, 28, 186-189.
- Punj, Brookes (2001), "Decision Constraints and Consideration-Set Formation in Consumer Durables," *Psychology & Marketing*, 18 (August), 843-863.

- Punj, Girish and Richard Brookes (2002), "The Influence Of Pre-Decisional Constraints On Information Search And Consideration Set Formation In New Automobile Purchases," *Internal Journal of Research in Marketing*, 19, 383-400.
- and Staelin, Richard (1983), "A Model of Consumer Information Search Behavior for New Automobiles," *Journal of Consumer Research*, 9, 366-380.
- Ratneshwar, S., Cornelia Pechmann and Allan D. Shocker (1996), "Goal-Derived Categories and the Antecedents of Across-Category Consideration," *Journal of Consumer Research*, 23 (December), 240-250.
- Roberts, John H. and James M. Lattin (1991), "Development and Testing of a Model of Consideration Set Composition," *Journal of Marketing Research*, 28 (November), 429-440.
- and ----- (1997), "Consideration: Review of Research and Prospects for Future Insights," *Journal of Marketing Research*, 34 (August), 406-410.
- Sawtooth Software, Inc. (1996), "ACA System: Adaptive Conjoint Analysis," ACA Manual, (Sequim, WA: Sawtooth Software, Inc.)
- (2008), "ACBC Technical Paper," (Sequim WA; Sawtooth Software, Inc.)
- Schmitt, Michael and Laura Martignon (2006), "On the Complexity of Learning Lexicographic Strategies," *Journal of Machine Learning Research*, 7, 55-83.
- Shao, Wei (2006), "Consumer Decision-Making: An Empirical Exploration of Multi-Phased Decision Processes," doctoral dissertation, Department of Philosophy, Griffith University.
- Shocker, Allen D., Moshe Ben-Akiva, B. Boccara, and P. Nedungadi (1991), "Consideration Set Influences on Customer Decision-Making and Choice: Issues, Models and Suggestions," *Marketing Letters*, 2, 181-198.
- Shugan, Steven M. (1980), "The Cost of Thinking," *Journal of Consumer Research*, 7, 2 (September), 99-111.
- Siddarth, S., Randolph E. Bucklin, and Donald G. Morrison (1995), "Making the Cut: Modeling and Analyzing Choice Set Restriction in Scanner Panel Data," *Journal of Marketing Research*, 33 (August), 255-266.
- Silinskaia, Daria, John R. Hauser, and Glen L. Urban (2009), "Adaptive Profile Evaluation to Identify Heuristic Decision Rules in 'Large' and Challenging Experimental Designs," NFORMS Marketing Science Conference, Ann Arbor, MI, June 2009.
- Silk, Alvin J. and Glen 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, Herbert A. (1955), "A Behavioral Model of Rational Choice," *The Quarterly Journal of Economics*, 69(1). 99-118.
- Srinivasan, V. (1988), "A Conjunctive-Compensatory Approach to The Self-Explication of Multiattributed Preferences," *Decision Sciences*, 295-305.

- and Gordon 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.
- Steckel, Joel H. and Russell S. Weiner, Randolph E. Bucklin, Benedict G.C. Dellaert, Xavier Drèze, Gerald Häubl, Sandy D. Jap, John D.C. Little, Tom Meyvis, Alan L. Montgomery, and Arvind Rangaswamy (2005) "Choice in Interactive Environments," *Marketing Letters*, 16, 3, 309-320.
- Svenson, O. (1979), "Process Descriptions of Decision Making," *Organizational Behavior and Human Performance*, 23, 86-112.
- Swait, Joffre (2001), "A Noncompensatory Choice Model Incorporating Cutoffs," *Transportation Research*, 35, Part B, 903-928.
- and Moshe 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.
- Tversky, Amos (1969), "Intransitivity of Preferences," *Psychological Review*, 76, 31-48.
- (1972), "Elimination by Aspects: A Theory of Choice," *Psychological Review*, 79, 4, 281-299.
- and Shmuel Sattath (1979), "Preference Trees," *Psychological Review*, 86, 6, 542-573.
- , Shmuel Sattath, and Paul Slovic (1987), "Contingent Weighting in Judgment and Choice," *Psychological Review*, 95 (July), 371-384.
- and Itamar Simonson (1993), "Context-Dependent Preferences," *Management Science*, 39 (October), 1179-1189.
- Urban, Glen. L., John. R. Hauser, and John. H. Roberts (1990), "Prelaunch Forecasting of New Automobiles: Models and Implementation," *Management Science*, Vol. 36, No. 4, (April), 401-421.
- and Gerald M. Katz, "Pre-Test Market Models: Validation and Managerial Implications," *Journal of Marketing Research*, Vol. 20 (August 1983), 221-34.
- Vroomen, Björn, Philip Hans Franses, and Erjen van Nierop (2004), "Modeling Consideration Sets And Brand Choice Using Artificial Neural Networks," *European Journal of Operational Research*, 154, 206-217.
- Wright, Peter and Fredrick Barbour (1977), "Phased Decision Making Strategies: Sequels to an Initial Screening," *TIMS Studies in the Management Sciences*, 6, 91-109
- Wu, Jianan and Arvind Rangaswamy (2003), "A Fuzzy Set Model of Search and Consideration with an Application to an Online Market," *Marketing Science*, 22 (Summer), 411-434.
- Yee, Michael, Ely Dahan, John R. Hauser, and James Orlin (2007), "Greedoid-Based Noncompensatory Inference," *Marketing Science*, 26 (July-August), 532-549.

Zhang, Jiao, Christopher K. Hsee, Zhixing Xiao (2006), "The Majority Rule in Individual Decision Making," *Organizational Behavior and Human Decision Processes*, 99, 102-111.