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The authors test methods, based on cognitively simple decision rules, that predict which products consumers select for their consideration sets. Drawing on qualitative research, the authors propose disjunctions-of-conjunctions (DOC) decision rules that generalize well-studied decision models, such as disjunctive, conjunctive, lexicographic, and subset conjunctive rules. They propose two machine-learning methods to estimate cognitively simple DOC rules. They observe consumers' consideration sets for global positioning systems for both calibration and validation data. They compare the proposed methods with both machine-learning and hierarchical Bayes methods, each based on five extant compensatory and noncompensatory rules. For the validation data, the cognitively simple DOC-based methods predict better than the ten benchmark methods on an information theoretic measure and on hit rates. The results are robust with respect to format by which consideration is measured, sample, and presentation of profiles. The article closes with an illustration of how DOC-based rules can affect managerial decisions.

Keywords: consideration sets, noncompensatory decisions, consumer heuristics, machine learning, conjoint analysis, cognitive simplicity, lexicography, decision theory

Disjunctions of Conjunctions, Cognitive Simplicity, and Consideration Sets

Consideration decisions are managerially important. For example, General Motors has invested heavily in product design and quality; in 2007, Buick tied Lexus for the top spot in J.D. Power and Associates' vehicle dependability ranking, and in 2008, Buick was the top U.S. brand in *Consumer Reports*. However, roughly half of U.S. consumers (64% in California) will not even consider a Buick. Because the typical consumer considers fewer than 10 vehicles when shopping for a new vehicle, top managers at General Motors are interested in understanding how consumers decide which 10 of the 350-plus make–model combinations to consider further. To direct strategies, they would like to model the features consumers use to screen products for further consideration. They would like a model that can forecast changes in consideration as a function of changes in product lines or changes in the features that are emphasized in marketing activities.

Two-stage, consider-then-choose decision rules are particularly relevant in the automobile market, but modeling and forecasting such decision rules is of general interest. When consumers face a large number of alternative products, as is increasingly common in today's retail and Web-based shopping environments, they typically screen the full set of products down to a smaller, more manageable consid-

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eration set, which they then evaluate further (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; Shocker et al. 1991; Wu and Rangaswamy 2003). Consideration sets for packaged goods typically comprise 3–4 products rather than the 30–40 products on the market (Hauser and Wernerfelt 1990; Urban and Hauser 2004). Forecasting consideration sets can explain approximately 80% of the explainable uncertainty in consumer decision making (assuming equally likely choice within the consideration set; Hauser 1978). In complex product categories, research suggests that at least some consumers use noncompensatory decision processes when evaluating many products and/or products with many features (e.g., Payne, Bettman, and Johnson 1988, 1993).

In this article, we explore machine-learning algorithms based on noncompensatory decision rules that model consumers' decisions in the consideration stage of a consider-then-choose process. We measure consideration directly for a moderately complex product, handheld global positioning systems (GPSs), and assuming a general form of noncompensatory decision rules, we attempt to model the noncompensatory patterns that best predict consumers' consideration decisions. The general form, disjunctions of conjunctions (DOC), is motivated by qualitative data and nests several previously studied rules. We argue further that modeling and controlling for cognitive simplicity enhances predictive ability.

We compare the DOC-based machine-learning algorithms with two sets of benchmarks. The first set includes alternative machine-learning algorithms that assume either compensatory decision rules or previously published noncompensatory decision rules. The second set includes hierarchical Bayes (HB) methods for the same compensatory and noncompensatory rules. In this product category, the proposed DOC-based machine-learning methods predict consideration sets better than the benchmarks using two metrics—hit rates and an information-theoretic measure. In almost all comparisons, predictions are significantly better statistically.

We demonstrate that the basic conclusions are robust with respect to format by which consideration is measured (four formats tested), sample (a German representative sample versus a U.S. student sample), and presentation of profiles (pictures versus text). We close by illustrating how the modeled noncompensatory patterns affect managerial decisions differently than additive decision rules.

NOTATION AND ESTABLISHED DECISION RULES

We focus on data in which respondents are asked to indicate which of several product profiles (32 in our experiments) they would consider. Respondents are free to select any size consideration set. In some formats, respondents classify each profile as considered or not considered; in other formats, they do not need to evaluate every profile.

We explore situations in which features are described by finitely many levels. Let j index the profiles, l index the levels, f index the features (sometimes called "attributes" in the literature), and h index the respondents. Let J, L, F, and H be the corresponding numbers of profiles, levels, features, and respondents. For ease of exposition only, we do not write J, L, and F as dependent (e.g., L_f). The models and estimation can (and do) handle such dependency, but the notation is cumbersome. Let $x_{jfl} = 1$ if profile j has feature f at level l; otherwise, $x_{jfl} = 0$. Let $\vec{x}_j$ be the binary vector (of length LF) describing profile j. Let $y_{hj} = 1$ if we observe that respondent h considers profile j; otherwise, $y_{hj} = 0$. Let $\vec{y}_h$ be the binary vector describing respondent h's consideration decisions.

Noncompensatory Decision Rules

Commonly studied noncompensatory rules include disjunctive, conjunctive, lexicographic, elimination-by-aspects, and subset conjunctive rules (e.g., Gilbride and Allenby 2004, 2006; Jedidi and Kohli 2005; Montgomery and Svenson 1976; Ordóñez, Benson, and Beach 1999; Payne, Bettman, and Johnson 1988; Yee et al. 2007). Subset conjunctive rules generalize disjunctive and conjunctive rules (Jedidi and Kohli 2005). For consideration decisions, they also generalize lexicographic rules and deterministic elimination-by-aspects because any implied ranking of products by lexicographic feature-level orders is indeterminate if only the consideration decision is observed (Hogarth and Karelaia 2005; Johnson, Meyer, and Ghose 1989; Montgomery and Svenson 1976; Payne, Bettman, and Johnson 1988; Tversky 1972).

Disjunctive rules. In a disjunctive rule, a profile is considered if at least one of the features is at an "acceptable" (or satisfactory) level. Let $a_{hfl} = 1$ if level l of feature f is acceptable to respondent h; otherwise, $a_{hfl} = 0$. Let $\vec{a}_h$ be the binary vector of acceptabilities for respondent h. A disjunctive rule states that respondent h considers profile j if $\vec{x}'_j\vec{a}_h \geq 1$.

Conjunctive rules. In a conjunctive rule, a profile is considered if *all* the features are at an acceptable level. (Conjunctive rules usually assume a larger set of acceptable levels than disjunctive rules, but this is not required.) Because the use in each rule is clear in context, we use the same notation: In a conjunctive rule, respondent h considers profile j if $\vec{x}'_j\vec{a}_h = F$.

Subset conjunctive rules. In a subset conjunctive rule, a profile is considered if at least S features are at an acceptable level. Using the same notation, respondent h considers profile j if $\vec{x}'_j\vec{a}_h \geq S$. A disjunctive rule is a special case in which S = 1, and because $\vec{x}'_j\vec{a}_h$ can never exceed F, a conjunctive rule is a special case in which S = F. We denote subset conjunctive rules by Subset(S). (Subset conjunctive rules are mathematically equivalent to "image-theory" rules in organizational behavior [see Ordóñez, Benson, and Beach 1999].)

Additive and q-Compensatory Decision Rules

Perhaps the most pervasively studied decision rules are additive rules. In an additive rule, consumers consider a profile if its "utility" is above some threshold, T_h, which accounts for search and processing costs. If $\vec{\beta}_h$ is the vector of partworths for respondent h, then h considers profile j if $\vec{x}'_j\vec{\beta}_h \geq T_h$. For estimation, we model errors in the decisions.

Many researchers have demonstrated that an additive partworth rule can mimic lexicographic, subset conjunctive, and conjunctive rules (e.g., Jedidi and Kohli 2005; Kohli and Jedidi 2007; Olshavsky and Acito 1980; Yee et al. 2007). To explore whether a model might predict better if it is constrained to be compensatory, we follow Bröder (2000) and Yee and colleagues (2007), who specify a q-compensatory model by constraining the additive model so that no feature's importance is more than q times as large as another feature's importance. (Hogarth and Karelaia [2005] and Martignon and Hoffrage [2002] use related constraints. A feature's importance is the difference between the maximum and the minimum partworths for that feature.)

DOC

To study consideration-set decisions, we began with a qualitative study that used in-depth interviewing of 39 automobile consumers who were asked to describe their consideration decisions for 100 real automobiles balanced to market data. All interviews were videotaped, and the videos were evaluated by independent judges who were blind to any hypotheses about consumers' decision rules (Hughes and Garrett 1990; Perreault and Leigh 1989). Most respondents made consideration decisions rapidly (89% averaged less than 5 seconds per profile), and most used noncompensatory decision rules (76%). Typically, consumers used conjunctive-like criteria defined on specific levels of features. However, some consumers would consider an automobile if it satisfied at least one of multiple conjunctive criteria (i.e., a disjunction of two or more conjunctions).

For example, the following respondent considered automobiles that satisfied *either* of two criteria. The first criterion is clearly conjunctive (good styling, good interior room, excellent mileage). The second criterion allows for cars that are "hot rods," which usually have poor interior room and poor mileage.

> [I would consider the Toyota Yaris because] the styling is pretty good, lot of interior room, mileage is supposed to be out of this world.
>
> I definitely [would] consider [the Infinity M-Sedan], though I would probably consider the G35 before the "M". I like the idea of a kind of a hot rod.

Depth interviewing is, by necessity, based on a small sample. From the sample, we could not determine whether multiple conjunctions were pervasive or limited to a subset of consumers. However, qualitative interviewing in the handheld GPS category also identified some consumers who used multiple conjunctions. A respondent might be willing to consider a GPS with a black-and-white (B&W) screen if the GPS was small and the screen was high resolution, but this same respondent would require a color screen on a large GPS. Such rules can be written as logical patterns: (B&W screen $\wedge$ small size $\wedge$ high resolution) $\vee$ (color screen $\wedge$ large size), where $\wedge$ is the logical "and" and $\vee$ is the logical "or." Patterns might also include negations ($\neg$); for example, a consumer might accept a B&W screen as long as the GPS is less than the highest price of \$399: (B&W screen $\wedge$ $\neg$\$399).

Formal Definition of DOC Rules

To study this phenomenon further, we formalize these qualitative insights with a class of decision rules that generalizes previously-proposed rules. Following Tversky (1972), we define an aspect as a binary descriptor, such as "B&W screen." A profile either has or does not have an aspect. A pattern is a conjunction of aspects or their negations, such as (B&W screen $\wedge$ $\neg$\$399). We define the size, s, of a pattern as the number of aspects in the pattern. For example, (B&W screen $\wedge$ $\neg$ \$399) has size s = 2. If p indexes patterns, we say that a profile j matches pattern p if profile j contains all aspects (or negations) in pattern p.

We study rules in which a respondent considers a profile if the profile matches one or more target patterns. Because each pattern is a conjunction, these logical rules are disjunctions of conjunctions. These DOC rules generalize disjunctive rules (disjunctions of patterns of size 1), conjunctive rules (patterns of size F), and subset conjunctive rules (patterns of size S).[1]

Let $w_{hp} = 1$ if pattern p is one of the patterns describing respondent h's decision rule, and let $m_{jp} = 1$ if profile j matches pattern p. Otherwise, w_{hp} and m_{jp} are zero. Let $\vec{w}_h$ and $\vec{m}_j$ be the corresponding binary vectors with length equal to the number of allowable patterns in a DOC rule. A DOC rule implies that respondent h considers profile j if and only if $\vec{m}'_j\vec{w}_h \geq 1$.

Cognitive Simplicity

The DOC rules generalize previously proposed noncompensatory decision rules, but they might be too general. For example, any profile can be described by a pattern of size F. Thus, any consideration set of size n can be fit perfectly with a disjunction of n conjunctions of size F. Fortunately, experimental evidence suggests that consumers make consideration decisions with relatively simple rules that enable them to make good decisions while avoiding excess cognitive effort (e.g., Bettman, Luce, and Payne 1998; Bröder 2000; Gigerenzer and Goldstein 1996; Gigerenzer, Todd, and the ABC Research Group 1999; Hogarth and Karelaia 2005; Martignon and Hoffrage 2002; Payne, Johnson, and Bettman 1988, 1993; Shugan 1980; Simon 1955). This perspective of simple, efficient, search-and-evaluation rules is consistent with economic theories of consideration-set formation that posit that consumers balance search costs with the option value of utility maximization (Hauser and Wernerfelt 1990; Roberts and Lattin 1991). To capture this "cognitive simplicity," we define DOC(S) rules as the set of DOC rules with maximum pattern length S. In addition, we either limit the number of patterns, P, or penalize DOC rules that have large P.

MACHINE-LEARNING APPROACHES TO IDENTIFY DOC PATTERNS

For a set of respondents and profiles, the basic data we observe are whether a respondent considers a profile (y_{hj}). We attempt to identify the patterns that predict best how respondent h evaluates profiles. Using a calibration sample, we seek patterns such that $\vec{m}'_j\vec{w}_h \geq 1$ whenever we observe that profile j is considered and such that $\vec{m}'_j\vec{w}_h = 0$ when-

[1]In the Web Appendix (http://www.marketingpower.com/jmrjune10), we formally demonstrate that (1) disjunctive rules, subset conjunctive rules of pattern length 1, and DOC rules of maximum pattern length 1 are equivalent; (2) conjunctive rules and subset conjunctive rules of pattern length F are equivalent and a subset of the DOC rule; and (3) subset conjunctive rules of pattern length S can be written as DOC rules, but there are DOC rules of maximum pattern length S that cannot be written as subset conjunctive rules of pattern length S.

ever we observe that profile j is not considered. (Recall that $\vec{m}_j$ and $\vec{w}_h$ are binary.)

The number of allowable DOC(S) patterns grows rapidly with S. For example, with the 16 binary features in the empirical test, there would be 32 patterns for S = 1, 512 for S = 2, 4992 for S = 3, and 34,112 for S = 4. There would be approximately 20 million patterns of length S = 10. With only 32 binary observations (consider versus not consider), there is serious concern about overfitting because the vector, $\vec{w}_h$, which we attempt to estimate, has a length equal to this large number of allowable patterns.

Machine learning is particularly suited to this pattern-matching task. Qualitative interviews suggest that it is not unreasonable for patterns to be up to length S = 4, which requires that we search more than 34,000 patterns to find those that best fit the data. Although we might place priors on each pattern and use Bayesian methods, we have not yet been able to develop a Bayesian representation in which the posterior is robust with respect to exogenously set priors for the large number of parameters. We leave exploration of Bayesian DOC models to further research.

Rather than producing posterior probabilities of pattern inclusion, we seek binary indicators of whether a pattern is in the best-fit solution. If the data are too noisy or the solution space is too large (even if we control for cognitive simplicity), predictions could overfit the data and predict poorly. To be sensitive to this concern, we compare models using predictive tests in which respondents face an entirely new set of profiles and report consideration for those profiles.

Cognitive Simplicity and Complexity Control

Although we used cognitive simplicity to motivate small S and P, such constraints or penalties have an alternative interpretation within machine learning—namely, complexity control (e.g., Cucker and Smale 2002; Evgeniou, Boussios, and Zacharia 2005; Hastie, Tibshirani, and Friedman 2003; Langley 1996; Vapnik 1998). Limiting the complexity of a model often reduces in-sample overfitting and enhances out-of-sample prediction. Both the behavioral explanation and the complexity-control motivation are consistent with the DOC(S) models—we cannot rule out either with the data in this study.

Sample Shrinkage

To further distinguish among potential patterns, we use data from the entire sample to help select patterns for respondent h. In an analogy to shrinkage, which enhances accuracy in HB models (e.g., Rossi and Allenby 2003), we favor patterns that fit the largest subset of respondents. Although shrinkage alone is sufficient motivation for use in our models, shrinkage is consistent with behavioral theories that suggest that simple rules have evolved because they work well in the general environment in which a sample of consumers often make decisions (e.g., Chase, Hertwig, and Gigerenzer 1998). These researchers hypothesize that consumers continue to use similar (simple) rules when faced with new decisions.

We now briefly summarize two machine-learning methods. Detailed equations are available in the Web Appendix (http://www.marketingpower.com/jmrjune10).

Mathematical Programming (DOCMP)

Because we seek the binary vector, $\vec{w}_h$, that best matches patterns in the calibration data, we formulate an integer program such that w_{hp} must be either 0 or 1 for all p. For respondent h, we define false positives, $FP_h(\vec{w}_h)$, as the number of profiles predicted to be considered but observed as not considered, and we define false negatives, $FN_h(\vec{w}_h)$, as the number of profiles predicted to be not considered but observed to be considered. In its most basic form, the integer program (DOCMP) would choose the $\vec{w}_h$ that minimizes the sum of false positives and false negatives for respondent h.

We enforce cognitive simplicity (complexity control) by limiting the search to patterns of length S or less and by penalizing pattern length, P. We include shrinkage with terms proportional to the sum of false positives and false negatives in the sample (sum over all respondents). Formally, the objective function is as follows:

$$\text{(1)} \quad \min_{\{\vec{w}_h\}} \left\{ FP_h(\vec{w}_h) + FN_h(\vec{w}_h) + \gamma_M \sum_{i=1}^{H} \left[FP_i(\vec{w}_h) + FN_i(\vec{w}_h) \right] + \gamma_c P \right\}.$$

Note that DOCMP is equivalent to a set-covering problem and, thus, is an NP-hard problem (Cormen et al. 2001). Fortunately, efficient greedy approximation algorithms have been developed and tested for this class of problems (Feige 1998; Lund and Yannakakis 1994). Alternatively, DOCMP can be solved approximately with a linear-programming relaxation in which we first allow $\vec{w}_h$ to be continuous on [0, 1] and then round up any positive w_{hj} that is above a threshold (see Hastie, Tibshirani, and Friedman 2003, and the references therein). In our estimations, we use both the greedy and the relaxation methods, choosing the solution that provides the best value of the objective function (using calibration data only, no data from the validation profiles).

The DOCMP requires three exogenous parameters: γ_M, which tells us how much to penalize a lack of sample-level fit; γ_c, which tells us how much to penalize the number of patterns; and S, which sets the maximum pattern length. One method to select these parameters is leave-one-out cross-validation (e.g., Cooil, Winer, and Rados 1987; Efron and Tibshirani 1997; Evgeniou, Pontil, and Toubia 2007; Hastie, Tibshirani, and Friedman 2003; Kearns and Ron 1999; Kohavi 1995; Shao 1993; Toubia, Evgeniou, and Hauser 2007; Zhang 2003). Specifically, for potential values of the exogenous "tuning" parameters, we leave out one profile from the calibration data, estimate $\vec{w}_h$, predict consideration for the left-out profile, and choose "tuning" parameters to minimize prediction errors on the holdout profiles. (No data from any holdout or validation observations are used in leave-one-out cross-validation.)

In the data, neither the leave-one-out cross-validation nor out-of-sample predictions are particularly sensitive to the choice of "tuning" parameters within ranges that roughly match a priori beliefs. Such robustness is consistent with Evgeniou, Pontil, and Toubia (2007). Specifically, we can choose any γ_M that is an arbitrarily small number such that sample-level consideration is used only to break ties among patterns. For γ_c, cross-validation (and predictive tests) varies little in the range $\gamma_c \in [1, 4.5]$. Similarly, we can select a cognitively simple S to be within ranges that we observe in qualitative interviews (S ~ 2, 3, 4). We report S = 4 for ease of exposition.

Logical Analysis of Data (LAD-DOC)

Logical analysis of data (LAD), which attempts to distinguish "positive" events from "negative" events, is another approach to generate patterns (Boros et al. 1997; Boros et al. 2000). We control cognitive simplicity by limiting the search to at most P patterns of at most size S. We define positive patterns as patterns that match at least one considered profile but no nonconsidered profile. Following the "bottom-up" approach that Boros and colleagues (2000) describe, we begin by generating minimal patterns of length one that match some considered profiles. If such patterns are not contained in any nonconsidered profile, they are positive patterns. Otherwise, we add aspects to the patterns one by one until we generate positive pattens, or until we reach maximum length (S). Next, we use a greedy algorithm to identify up to P positive patterns that best fit the data, breaking ties first by giving preference to shorter patterns and then patterns that are positive most often in the sample. The union of these positive patterns is a DOC rule. Thus, LAD-DOC provides a contrast to DOCMP. It is simpler to formulate and takes less time to run, but it shares the characteristics of selecting patterns that best fit the data subject to cognitive simplicity (S, P) and shrinkage (break ties to fit sample-level consideration). A potential weakness is that the implementation of LAD focuses primarily on avoiding false positives (in the calibration data) rather than a combination of false positives and false negatives. For comparability to DOCMP, we set S = 4 and P = 2, but out-of-sample predictions are comparable for P ~ 2, 3, or 4 and S ~ 4 or 5.

BENCHMARKS

As benchmarks, we choose five decision rules. We estimate these rules with both machine-learning and HB methods. The decision rules are as follows:

1. Additive partworth rules,
2. Additive q-compensatory rules,
3. Disjunctive rules,
4. Conjunctive rules, and
5. Subset conjunctive rules.

The machine-learning estimations use objective functions comparable to Equation 1. For the additive and q-compensatory rules, we penalize the sum of the partworths rather than the number of patterns. Detailed formulations are available in the Web Appendix (http://www.marketingpower.com/jmrjune10).

The HB methods mimic extant methods to the greatest extent possible. For the additive and q-compensatory rules, we use standard HB choice-based conjoint formulations adapted to the dependent variable (consideration versus not). We use rejection sampling to enforce the q-compensatory constraint (e.g., Allenby, Arora, and Ginter 1995). For subset conjunctive rules, we modify an algorithm that Gilbride and Allenby (2004) developed. The modifications reflect differences in data and generalization (S = 1 or F in Gilbride and Allenby [2004]). As data, we observe consideration directly, while it is a latent construct in Gilbride and Allenby's formulation. To address unordered multilevel features, we do not impose constraints that levels within a feature are ordered. Detailed HB formulations are available in the Web Appendix (http://www.marketingpower.com/jmrjune10).

For the subset conjunctive rules, we select S = 4 to be consistent with the DOC rules. (Predictive tests for other values of S are available on request.[2]) In addition to detailed formulations, the Web Appendix (http://www.marketingpower.com/jmrjune10) also contains simulations that compare some of the benchmarks with DOC-based methods on synthetic data.[3]

EMPIRICAL APPLICATION: GPS

We chose to study GPSs because the number of features and brands available is sufficiently large that we might expect some noncompensatory decision rules. Figure 1 illustrates 16 features that consumers use to evaluate handheld GPSs. We chose these features as the most important on the basis of two pretests of 58 and 56 consumers, respectively. Of the features, 10 are represented by text and icons, and the remaining 6 are represented by text and visual cues.

Using the 16 features, we generated an orthogonal design of 32 GPS profiles.[4] We then developed four alternative formats to measure consideration. We developed these respondent task formats on the basis of qualitative pretests to approximate the shopping environment for GPSs. Each respondent task format was implemented in a Web-based survey and was pretested extensively with more than 55 potential respondents from the target market. At the end of the pretests, respondents found the tasks easy to understand and reported that the task formats were reasonable representations of the handheld GPS market.

We invited two sets of respondents to complete the Web-based tasks: a representative sample of German consumers who were familiar with handheld GPSs and a U.S.-based student sample. We first describe the results from the primary format using the German sample of representative consumers. We then discuss the other formats, the student sample, and a text-only version.

Figure 2 provides screenshots in English and German for the basic format. A "bull pen" is on the far left. As respondents move their cursor over a generic image in the bull pen, a GPS appears in the middle panel. If respondents click on the generic image, they can evaluate the GPS in the middle panel and decide whether to consider it. If they decide to consider the GPS, its image appears in the right panel. Respondents can toggle between current consideration sets and their current nonconsidered sets. There are many ways

[2]The basic relative comparisons with DOC-based models are similar for S ~ 1, 2, 3, or 4.

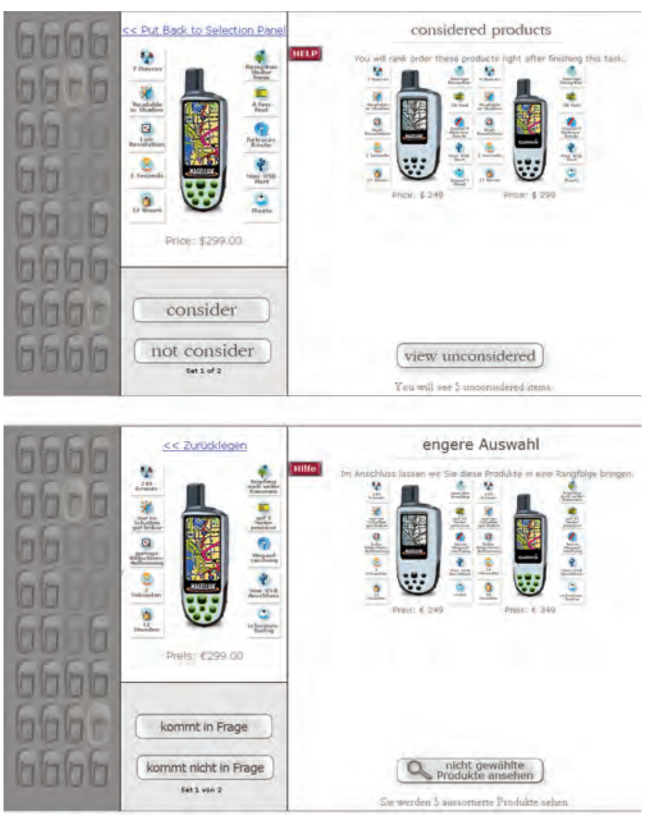
[3]The simulations are consistent with intuition and with empirical results in the domain suggested by the empirical data. For example, when the data are generated with a particular decision rule, the estimation models that assume that decision rule tend to predict (out of sample) best.

[4]To make the task realistic and to avoid dominated profiles (Johnson, Meyer, and Ghose 1989), we manipulated price as a two-level price increment. Profile prices were based on this increment plus additive feature-based costs. We return to the issue of orthogonal designs at the end of this section.

Figure 1
FEATURES OF HANDHELD GPSs

they can change their mind—for example, putting a GPS back or moving it from the consideration set to the nonconsidered set, or vice versa. In this format, respondents continue until all GPSs are evaluated.

Figure 2
CONSIDERATION TASK IN ONE OF THE FORMATS (ENGLISH AND GERMAN)



Before respondents made consideration decisions, they reviewed screens that described GPSs in general and each of the GPS features. They also viewed instruction screens for the consideration task and instructions that encouraged incentive compatibility. Following the consideration task, respondents ranked profiles within the consideration set (these data are not used in this article) and then completed tasks designed to cleanse their memory. These tasks included short brainteaser questions that directed respondents' attention away from GPSs. Following the memory-cleansing tasks, respondents completed the consideration task a second time but for a different orthogonal set of GPSs. These second consideration decisions are validation data and are not used in the estimation of any rules.

Respondents were drawn from a Web-based panel of consumers maintained by the GfK Group. Initial screening eliminated respondents who had no interest in buying a GPS and no experience using a GPS. Respondents who completed the questionnaire received an incentive of 200 points (or *punkte*, in accordance with GfK) toward general prizes and were entered into a lottery in which they could win one of the GPSs (plus cash) that they considered. This lottery was designed to be incentive aligned, as in Ding (2007) and Ding, Grewal, and Liechty (2005). (Respondents who completed only the screening questionnaire received 15 *punkte*.)

In total, 2320 panelists were invited to answer the screening questions. The incidence rate (percentage eligible) was 64%, the response rate was 47%, and the completion rate was 93%. Respondents were assigned randomly to one of the five task formats (the basic format in Figure 2, three alternative formats, and a text-only format). After eliminating respondents who had null consideration sets or null nonconsidered sets in the estimation task, we retained 580 respondents. The average size of the consideration set (estimation data) for the task format in Figure 2 was 7.8 profiles. There was considerable variation among respondents (SD = 4.8 profiles). The average size of the consideration set in the validation task was smaller (7.2 profiles) but not significantly different. Validation consideration-set sizes had an equally large standard deviation (4.8 profiles).

PREDICTIVE TESTS

Criteria to Compare DOCMP, LAD-DOC, and the Benchmarks

Hit rate is an intuitive measure that is used commonly when comparing predictive ability. However, with average consideration sets at approximately 7.2 of 32 (22.5%), a null model that predicts that no GPSs will be considered will achieve a hit rate of 77.5%. Thus, we follow Srinivasan (1988), Srinivasan and Park (1997), and Payne, Bettman, and Johnson (1993, p. 128) and report the percentage improvement relative to a random-prediction null model. Percentage improvement is a linear transformation of hit rate, but it is easier to interpret.

More critically, the apparent strong performance of "predict nothing considered" suggests that we gain insight with statistics that reward models that actually try to predict consideration. The ability to predict the consideration-set size can reject bad models, but it is not sufficient to evaluate a good model. A null model of random prediction (proportional to calibration consideration-set size) predicts the validation consideration-set size accurately but achieves a low hit rate of 65.3% and provides no useful information (0% relative hit rate improvement).

Instead, we consider a statistic that is sensitive to false positive predictions, false negative predictions, *and* predicted consideration-set sizes in the validation data. In particular, we use the Kullback-Leibler divergence (K-L), which measures the expected gain in Shannon's information measure relative to a random model (Chaloner and Verdinelli 1995; Kullback and Leibler 1951; Lindley 1956).[5] The K-L percentage is 0% for both the random null model and the "predict nothing considered" null model. It is 100% for perfect prediction. The K-L percentage rewards models that predict the consideration-set size correctly *and* favors a mix of false positives and false negatives that reflect true consideration sets over those that do not. It discriminates among models even when the hit rates might otherwise be equal. Together, the three statistics—hit rate, relative hit rate improvement, and the K-L percentage—provide a means to assess relative predictive ability (DOC-based models versus the benchmarks).

Predictive Comparison of DOCMP, LAD-DOC, and the Benchmarks

Table 1 summarizes the ability of each estimation method to predict consideration for the validation task. Focusing on the comparison of DOC-based models with the benchmarks, we find that DOC-based predictions are best or not significantly different than best on both hit rates and K-L percentage measures and better than all benchmark estimation methods on both measures. Furthermore, LAD-DOC predicts slightly better than DOCMP, but the difference is not significant.

Among the benchmarks, the additive-rule models predict well, with the machine-learning version predicting significantly better than the HB version on both hit rate and K-L percentage ($t = 2.6$, $p < .02$; $t = 3.7$, $p < .01$, respectively). While the DOC-based methods are best or not significantly different than best on all comparisons, the machine-learning additive model is within 1–2 percentage points on hit rate.[6] This is consistent with prior results on the robustness of the linear model for empirical data (e.g., Dawes 1979; Dawes and Corrigan 1974) and consistent with the ability of an additive rule to nest some noncompensatory rules.

[5]Formulae for K-L percentage for consideration-set prediction are available in the Web Appendix (http://www.marketingpower.com/jmrjune10). K-L acts for 0-versus-1 predictions much like U^2 does for probabilistic predictions (Hauser 1978).

[6]We find that LAD-DOC is significantly better than the best (machine-learning) additive model on both hit rate and K-L divergence ($t = 2.4$, $p < .02$; $t = 4.6$, $p < .01$), and DOCMP is better, but not quite significantly so, on hit rate and significantly better on K-L divergence ($t = 1.9$, $p = .06$; $t = 4.1$, $p < .01$). One reason the additive model does less well on the K-L percentage is that it underpredicts the consideration-set size. We examine the predictive ability of the additive model further in the next section.

Table 1

EMPIRICAL COMPARISON OF ESTIMATION METHODS (REPRESENTATIVE GERMAN SAMPLE, TASK FORMAT IN FIGURE 2)

Estimation Method	*Overall Hit Rate (%)*	*Relative Hit Rate Improvement (%)*	*K-L Divergence Percentage (%)*
HB Benchmarks			
Conjunctive (S = 16)	77.7	35.6	6.2
Disjunctive (S = 1)	66.7	3.8	17.8
Subset conjunctive (S = 4)	75.4	29.0	24.7
q-Compensatory	73.4	37.6	14.6
Additive	78.5	38.0	15.0
Machine-Learning Benchmarks			
Conjunctive (S = 16)	52.6	–36.8	13.3
Disjunctive (S = 1)	77.5	35.6	8.1
Subset conjunctive (S = 4)	73.7	24.3	6.3
q-Compensatory	76.2	31.3	6.3
Additive	80.6	44.0	23.0
DOC-Based Estimation Methods			
DOCMP (S = 4)	81.9*	47.8*	32.0*
LAD-DOC (S = 4, P = 2)	82.2*	48.6*	34.6*

*Best or not significantly different than the best at the .05 level.

Notes: Hit rate is the number of profiles predicted correctly, divided by 32.

Estimations based on the DOC generalization predict significantly better than the noncompensatory benchmarks, suggesting that the generalization improves predictions for at least some of the respondents.[7] The unconstrained additive models, which can represent both q-compensatory and many of the noncompensatory models, predict better than the q-compensatory models on both measures, significantly so for the machine-learning algorithms (for hit rates, $t = 2.1$, $p < .04$; for K-L, $t = 9.4$, $p < .01$). At the level of the individual respondent, some respondents are fit much better with an unconstrained model, and some are fit much better with a q-constrained model. Further research might investigate correlates of these individual differences.

For brevity, we do not elaborate further on comparisons among the benchmarks themselves. The data are available for readers who want to explore machine learning, HB, or other methods for the benchmark rules.

Empirical Evidence Is Consistent with Cognitive Simplicity

Although DOCMP and LAD-DOC are designed to favor cognitive simplicity, unconstrained estimation could conceivably predict better. We reestimated DOCMP with the γs equal to zero and LAD-DOC without the S and P constraints. For both models, the hit rates are significantly better for the penalized/constrained estimation ($p < .01$ versus 75.7% DOCMP without γs; $p < .01$ versus 80.4% LAD-DOC without constraints, respectively). Cognitive simplicity also improves the K-L percentage, but the improvements are not quite significant ($p < .16$ versus 29.6%; $p = .07$ versus 32.5%, respectively, for unconstrained DOCMP and LAD-DOC). These results are consistent with a hypothesis that predictions improve when cognitive simplicity is enforced, though the marginal significance for K-L percentages suggests that the cognitive simplicity hypothesis is worth further testing in other contexts.

Despite the large number of potential patterns, DOC-based estimation chose relatively simple rules for the data. The LAD-DOC predictions do not improve significantly, and often degrade, as we increase either pattern length (S) or the number of patterns (P). For DOCMP, 7.1% of the respondents are represented as using two patterns; the remainder are represented with a single pattern. The increased flexibility of the DOC-based estimation methods seems to improve predictive ability relative to alternative noncompensatory rules and their corresponding estimation methods, even though only 7.1% of the respondents are modeled with two patterns.

Sensitivity to Orthogonal Designs

Significant research in marketing exists on efficient experimental designs for choice-based conjoint experiments (Arora and Huber 2001; Huber and Zwerina 1996; Kanninen 2002; Toubia and Hauser 2007), but we are unaware of any research on efficient experimental designs for consideration decisions or for the estimation of cognitively simple DOC rules. When decisions are made with respect to the full set of 32 profiles, aspects are uncorrelated up to the resolution of the design, and if there were no errors, we should be able to identify DOC patterns accordingly. However, when profiles are removed, aspects may no longer be uncorrelated, and patterns may not be defined uniquely. As a mild test, we reestimated three models—DOCMP, machine-learning additive, and HB additive—with only 17 of the 32 most popular profiles (Numbers 16 and 17 were tied). The results show that DOCMP remained significantly better on the K-L percentages and best or not significantly different than best on hit rates, even though we are now estimating the models with approximately half the observations per respondent.

Until the issue of optimal DOC consideration experimental designs is resolved, the performance of DOC-based estimation methods remains a conservative predictive test. Improved or adaptive experimental designs might improve performance.

Summary of Empirical Results

The DOC-based estimation appears to predict hit rates well and to provide information (K-L percentage) about consideration decisions on validation data. Predictions appear to be better with DOC-based estimation than with any of the other five decision rules for both machine-learning and HB estimation, though an unconstrained machine-learning additive model (which can represent some noncompensatory rules) comes close. Some of this improvement is due to cognitive simplicity.

TARGET POPULATION, TASK FORMAT, AND PROFILE REPRESENTATION

We examine hypotheses that the predictive ability is unique to the task format, to the GfK respondents, or to the way we present profiles. We discuss each in turn.

Variations in Task Formats

With the format analyzed in the previous section, respondents must evaluate every profile ("evaluate all profiles"). However, such a restriction may be neither necessary nor descriptive. For example, Ordóñez, Benson, and Beach (1999) argue that consumers screen products by rejecting products they would not consider further. Because choice rules are context dependent (e.g., Payne, Bettman, and Johnson 1993), the task format could influence the propensity to use a DOC rule.

To examine context sensitivity, we tested alternative task formats. One format asked respondents to indicate only the profiles they would consider ("consider only"); another asked respondents to indicate only the profiles they would reject ("reject only"). The tasks were otherwise identical to "evaluate all profiles." We also tested a "no-browsing" format, in which respondents evaluated profiles sequentially (in a randomized order). Representative screenshots for these formats, as well as feature introduction screenshots and instruction screenshots, are available in the Web Appendix (http://www.marketingpower.com/jmrjune10).

The predictive results mimic the results in Table 1.[8] On the K-L percentages, both DOC-based estimation methods were significantly better than all benchmarks on all four for-

[7]We note the poor performance of the machine-learning subset conjunctive model with S = 16. With S = 16 and a goal of choosing 0 versus 1 for w_{hp}, the subset conjunctive integer program tends to overfit the calibration data.

[8]Tables for the other formats are available in the Web Appendix (http://www.marketingpower.com/jmrjune10).

mats. On hit rate, at least one of the DOC-based estimation methods was best on all formats, significantly better than all benchmarks for the majority of the formats (three of four), and significantly better than nine of the ten benchmarks for the remaining format. On hit rate, the only estimation method that did not differ significantly from a DOC-based estimation method on that one format was the machine-learning additive model—a result similar to that which we observed in Table 1. To test DOC-based methods further, we merged the data from the four formats and compared DOCMP and LAD-DOC hit rates with the additive machine-learning method. When the hit rate data are merged, both DOCMP and LAD-DOC predict significantly better than the additive machine-learning method ($t = 4.4$, $p < .01$; $t = 3.0$, $p < .01$).

As the evaluation cost theory of consideration-set formation predicts, respondents considered fewer profiles when the relative evaluation cost (for consideration) was higher: 4.3 profiles in "consider only," 7.8 in "evaluate all," and 10.6 in "reject only." As the theory of context dependence predicts, the propensity to use a second DOC pattern varied as well. In addition, disjunctions were more common when consideration sets were larger: 0% for "consider only," 7.1% for "evaluate all," and 9.8% for "reject only." Although the data cannot distinguish whether these differences are due to the size of the consideration set or due to differential evaluation costs induced by task variation, they illustrate how the predictive tests complement more direct (but possibly more intrusive) experimental measures.

U.S. Student Sample Versus Representative German Sample

We replicated the evaluate-all-profiles GPS measurement with a sample of MBA students at a U.S. university. Students were invited to an English-language Web site (e.g., first panel of Figure 1). As incentives, and to maintain incentive compatibility, they were entered in a lottery with a 1-in-25 chance of winning a laptop bag worth \$100 and a 1-in-100 chance of winning a combination of cash and one of the GPSs that they considered. The response rate for U.S. students was lower (26%), and on average, consideration-set sizes were larger. Despite the differences in sample, response rate, incentives, and consideration-set size, DOCMP and LAD-DOC predicted validation data best (or were not significantly different than the best) on both hit rates and K-L percentages. (Again, the best benchmark was the additive machine-learning model. Lower sample sizes for the U.S. sample made it more difficult to distinguish differences.)

Text-Only Versus Visual Representation of the GPS Profiles

The profile representations in Figure 1 were designed by a professional graphic artist and were pretested extensively. Pretests suggested which features should be included in the JPEGs and which features should be included as satellite icons. Nonetheless, it is possible that the relative predictive ability of the estimation methods depends on the specific visual representations of the profiles. To examine this hypothesis, we included a task format that was identical to the task in "consider all profiles," except that all features were described by text rather than pictures, icons, and text. Again, the DOC-based estimation methods are the best predictive methods—significantly better on K-L percentages and best or not significantly different than the best on hit rates—and again, the additive machine-learning method does as well on hit rate but not the K-L percentage. We cannot distinguish with the data whether this is a text-only effect or a result consistent with the analyses of the other formats. Notably, there is no significant difference in hit rates or K-L percentages between picture representations and text representations for either DOCMP or LAD-DOC.

Summary of Robustness Tests

The relative predictive ability of the tested methods appears to be robust with respect to the following:

- Format of the respondent task (evaluate all profiles, consideration only, rejection only, or no browsing),
- Respondent sample (representative German versus U.S. student), and
- Presentation of the stimuli (pictures versus text).

MANAGERIAL IMPLICATIONS AND DIAGNOSTICS

We were motivated to study consideration-set decisions with a managerial challenge: How can a firm increase the likelihood that its products will be considered? We hope that by estimating DOC-based models, we might gain insight to help a firm enhance consideration. If the improved predictive ability of DOC-based models holds up to further testing, market-response simulators using DOC-based models might be more accurate than market-response simulators based on conjunctive, disjunctive, subset conjunctive, q-compensatory, or additive-rule decision rules (for a discussion of using predictive models to evaluate strategies, see Geisser 1993). To illustrate how models affect managerial decisions differently, we compare the simulated value of feature improvements between estimated DOC rules and estimated additive rules. (The data are available for readers who want to explore other comparisons.)

Changes in Market Share as a Function of Feature Improvements

Ofek and Srinivasan (2002, p. 401) propose that a value of a feature should be defined as "the incremental price the firm would charge per unit improvement in the product attribute (assumed to be infinitesimal) if it were to hold market share (or sales) constant." In DOC rules, features and price levels are discrete; thus, we modify this definition slightly. We compute the incremental improvement in market share if a feature is added for an additional \$50 in price. Because this calculation is sensitive to the base product, we select the features of the base product randomly. We illustrate two of the many differences between DOC rules and additive rules. In both situations, the recommended managerial decision depends on whether consumers consider products using the estimated DOC rules or the estimated additive rules.

Example 1. The DOC rules predict that consideration share will increase if we switch to the Garmin GPS and raise the price by \$50, but compensatory rules predict that consideration share will decrease. To understand this difference intuitively, we recognize that the estimated DOC rules imply that 12% of the respondents screen on brand, and of those, 82% screen on Garmin. The remaining respondents screen on other features. With an additive partworth rule, 54% of the respondents have slightly higher partworths for the Magellan GPS. With DOC rules, the advantage to Garmin comes from the 12% who screen on brand, but with additive rules, the advantage to Magellan comes a little from all the respondents in the sample.

Example 2. Additive rules predict that "extra bright" is the highest-valued feature improvement, yielding an 11% increase for the $50 price. However, the DOC rules predict a much smaller improvement (2%) because many of the respondents who screen on extra bright also eliminate GPSs with the higher price.

Diagnostic Summaries of DOC Rules

Diagnostic summaries of additive partworths have been developed through decades of application. Recent developments have added heterogeneity with corresponding challenges in how best to summarize heterogeneity to managers. Diagnostic summaries of noncompensatory decision rules are relatively nascent. Academics and practitioners are still evolving the best way to summarize such rules for managers.

This challenge is exacerbated for DOC rules. Even with cognitive simplicity (S = 4), there are 34,112 potential DOC patterns. Listing each pattern that matches consideration in a sample of respondents is not nearly as diagnostic as the feature-improvement simulations, which aggregate across identified patterns. As a first attempt, we examined summaries of first- and second-order inclusion. (Gilbride and Allenby [2004] and Yee and colleagues [2007] report first-order inclusion.) For example, the mini-USB port appeared in at least one DOC conjunction for 36% of the respondents. Extra-bright displays (25%) and color displays (21%) were the next-highest contributors. With second-order inclusions, for example, respondents who want a long battery life also want a mini-USB port (50%) and a color display (40%). Such first- and second-order conjunctive inclusions provide insight that complements DOC model–based market-response simulators. As in the market-response simulations, these simple diagnostics vary from what might be inferred from additive partworths.

We hope that such diagnostic information combined with market-response simulators will help managers evaluate product line changes and marketing activities. With more experience, researchers might develop more intuitive ways to summarize DOC patterns for managers.

SUMMARY AND FUTURE DIRECTIONS

Consideration sets have become relevant to managerial decisions in many product categories, and whenever there are many products available and/or products are described by many features and levels, extant research suggests that consumers use noncompensatory decision rules to make consideration decisions. Research further suggests that such decision rules are often cognitively simple. We hope we have contributed to these literature streams.

Drawing on qualitative research, we propose a generalization of established noncompensatory decision rules: DOC. We posit further that DOC rules will be cognitively simple and that models that attempt to represent cognitively simple DOC rules will predict better than models that do not. We examine two machine-learning estimation methods, DOCMP and LAD-DOC, and compare predictions with five decision-rule models as implemented by both machine-learning and HB estimation methods.

The preponderance of the empirical evidence in this article suggests that DOC rules and both estimation algorithms are worth further investigation. Both are significantly better on K-L percentages for all ten benchmarks, all four respondent task formats, German and U.S. data, and both highly visual and text-only stimuli. We obtain the same perspective with hit rates with one important exception. The machine-learning additive method does almost as well for some formats, a result that is consistent with the known robustness of the additive model and with ability of the additive model to represent some noncompensatory decision rules.

The results must be considered hypotheses for further testing. The handheld GPS category has many features, and at the time of testing, it was relatively new to the respondents. This provided a "proof-of-concept" test for DOC-based methods. In more familiar or simpler categories, additive models might suffice. Conversely, more complex categories, such as automobiles, might favor DOC rules.

We chose two methods to estimate DOC rules. There are likely others. For example, decision trees can also represent DOC rules (Breiman et al. 1984; Currim, Meyer, and Le 1988). If researchers can develop a way to model cognitive simplicity on decision trees, this approach might prove promising. If features are continuous, DOC rules are similar to specific interactions in a multilinear decision rule (Bordley and Kirkwood 2004; Mela and Lehmann 1995). With sufficient creativity and experimentation, researchers might extend finite-mixture, Bayesian, simulated maximum likelihood, Markov, or kernel estimators to estimate cognitively simple continuous DOC analogs (Evgeniou, Boussios, and Zacharia 2005; Hauser and Wisniewski 1982; Mela and Lehmann 1995; Rossi and Allenby 2003; Swait and Erdem 2007).

Finally, we focused on the consideration stage of a consider-then-choose rule. The DOC rules might also apply to the choice stage. A model that is DOC in the first stage and compensatory in the second stage might also be investigated. There is a rich history in marketing of two-stage models in which consideration is a latent, unobserved construct (e.g., Andrews and Srinivasan 1995; Gensch 1987; Gilbride and Allenby 2004; Siddarth, Bucklin, and Morrison 1995; Swait and Erdem 2007). We believe that DOC rules combined with cognitive simplicity could complement these lines of research.

REFERENCES

Allenby, Greg M., Neeraj Arora, and James L. Ginter (1995), "Incorporating Prior Knowledge into the Analysis of Conjoint Studies," *Journal of Marketing Research*, 32 (May), 152–62.

Andrews, Rick 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.

Arora, Neeraj and Joel Huber (2001), "Improving Parameter Estimates and Model Prediction by Aggregate Customization in Choice Experiments," *Journal of Consumer Research*, 28 (September), 273–83.

Bettman, James R., Mary Frances Luce, and John W. Payne (1998), "Constructive Consumer Choice Processes," *Journal of Consumer Research*, 25 (3), 187–217.

Bordley, Robert F. and Craig W. Kirkwood (2004), "Multiattribute Preference Analysis with Performance Targets," *Operations Research*, 52 (November–December), 823–35.

Boros, Endre, Peter L. Hammer, Toshihide Ibaraki, and Alexander Kogan (1997), "Logical Analysis of Numerical Data," *Mathematical Programming*, 79 (August), 163–90.

———, ———, ———, ———, Eddy Mayoraz, and Ilya Muchnik (2000), "An Implementation of Logical Analysis of Data," *IEEE Transactions on Knowledge and Data Engineering*, 12 (2), 292–306.

Breiman, Leo, Jerome H. Friedman, Richard A. Olshen, and Charles J. Stone (1984), *Classification and Regression Trees*. Belmont, CA: Wadsworth.

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), 1332–46.

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), 163–73.

Chaloner, Kathryn and Isabella Verdinelli (1995), "Bayesian Experimental Design: A Review," *Statistical Science*, 10 (3), 273–304.

Chase, Valerie M., Ralph Hertwig, and Gerd Gigerenzer (1998), "Visions of Rationality," *Trends in Cognitive Sciences*, 2 (June), 206–214.

Cooil, Bruce, Russell S. Winer, and David L. Rados (1987), "Cross-Validation for Prediction," *Journal of Marketing Research*, 24 (August), 271–79.

Cormen, Thomas H., Charles E. Leiserson, Ronald L. Rivest, and Clifford Stein (2001), *Introduction to Algorithms*, 2d ed. Cambridge, MA: MIT Press.

Cucker, Felipe and Steve Smale (2002), "On the Mathematical Foundations of Learning," *Bulletin of the American Mathematical Society*, 39 (1), 1–49.

Currim, Imran S., Robert J. Meyer, and Nhan T. Le (1988), "Disaggregate Tree-Structured Modeling of Consumer Choice Data," *Journal of Marketing Research*, 25 (August), 253–65.

Dawes, Robyn M. (1979), "The Robust Beauty of Improper Linear Models in Decision Making," *American Psychologist*, 34 (7), 571–82.

——— and Bernard Corrigan (1974), "Linear Models in Decision Making," *Psychological Bulletin*, 81 (2), 95–106.

DeSarbo, Wayne S., Donald R. Lehmann, Gregory Carpenter, and Indrajit Sinha (1996), "A Stochastic Multidimensional Unfolding Approach for Representing Phased Decision Outcomes," *Psychometrika*, 61 (3), 485–508.

Ding, Min (2007), "An Incentive-Aligned Mechanism for Conjoint Analysis," *Journal of Marketing Research*, 44 (May), 214–23.

———, Rajdeep Grewal, and John Liechty (2005), "Incentive-Aligned Conjoint Analysis," *Journal of Marketing Research*, 42 (February), 67–82.

Efron, Bradley and Robert Tibshirani (1997), "Improvements on Cross-Validation: The .632+ Bootstrap Method," *Journal of the American Statistical Association*, 92 (June), 548–60.

Evgeniou, Theodoros, Constantinos Boussios, and Giorgos Zacharia (2005), "Generalized Robust Conjoint Estimation," *Marketing Science*, 24 (3), 415–29.

———, Massimiliano Pontil, and Olivier Toubia (2007), "A Convex Optimization Approach to Modeling Heterogeneity in Conjoint Estimation," *Marketing Science*, 26 (November–December), 805–818.

Feige, Uriel (1998), "A Threshold of ln n for Approximating Set Cover," *Journal of the Association for Computing Machinery*, 45 (4), 634–52.

Geisser, Seymour (1993), *Predictive Inference: An Introduction*. New York: Chapman & Hall.

Gensch, Dennis H. (1987), "A Two-Stage Disaggregate Attribute Choice Model," *Marketing Science*, 6 (Summer), 223–31.

Gigerenzer, Gerd and Daniel G. Goldstein (1996), "Reasoning the Fast and Frugal Way: Models of Bounded Rationality," *Psychological Review*, 103 (4), 650–69.

———, Peter M. Todd, and the ABC Research Group (1999), *Simple Heuristics That Make Us Smart*. Oxford: Oxford University Press.

Gilbride, Timothy J. and Greg M. Allenby (2004), "A Choice Model with Conjunctive, Disjunctive, and Compensatory Screening Rules," *Marketing Science*, 23 (3), 391–406.

——— and ——— (2006), "Estimating Heterogeneous EBA and Economic Screening Rule Choice Models," *Marketing Science*, 25 (September–October), 494–509.

Hastie, Trevor, Robert Tibshirani, and Jerome H. Friedman (2003), *The Elements of Statistical Learning*. New York: Springer.

Hauser, John R. (1978), "Testing the Accuracy, Usefulness and Significance of Probabilistic Models: An Information Theoretic Approach," *Operations Research*, 26 (May–June), 406–421.

——— and Birger Wernerfelt (1990), "An Evaluation Cost Model of Consideration Sets," *Journal of Consumer Research*, 16 (March), 393–408.

——— and Kenneth J. Wisniewski (1982), "Dynamic Analysis of Consumer Response to Marketing Strategies," *Management Science*, 28 (May), 455–86.

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 (December), 1860–72.

Huber, Joel and Klaus Zwerina (1996), "The Importance of Utility Balance in Efficient Choice Designs," *Journal of Marketing Research*, 33 (August), 307–317.

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), 185–95.

Jedidi, Kamel and Rajeev Kohli (2005), "Probabilistic Subset-Conjunctive Models for Heterogeneous Consumers," *Journal of Marketing Research*, 42 (November), 483–94.

———, ———, and Wayne S. DeSarbo (1996), "Consideration Sets in Conjoint Analysis," *Journal of Marketing Research*, 33 (August), 364–72.

Johnson, Eric J., Robert J. Meyer, and Sanjoy Ghose (1989), "When Choice Models Fail: Compensatory Models in Negatively Correlated Environments," *Journal of Marketing Research*, 26 (August), 255–90.

Kanninen, Barbara J. (2002), "Optimal Design for Multinomial Choice Experiments," *Journal of Marketing Research*, 39 (May), 214–27.

Kearns, Michael and Dana Ron (1999), "Algorithmic Stability and Sanity-Check Bounds for Leave-One-Out Cross-Validation," *Neural Computation*, 11 (6), 1427–53.

Kohavi, Ron (1995), "A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection," in *Proceedings of the 14th International Joint Conference on Artificial Intelligence*, Vol. 2. San Francisco: Morgan Kaufmann, 1137–43.

Kohli, Rajeev and Kamel Jedidi (2007), "Representation and Inference of Lexicographic Preference Models and Their Variants," *Marketing Science*, 26 (3), 380–99.

Kullback, Solomon and Richard A. Leibler (1951), "On Information and Sufficiency," *Annals of Mathematical Statistics*, 22 (1), 79–86.

Langley, Pat (1996), *Elements of Machine Learning*. San Francisco: Morgan Kaufmann.

Lindley, Dennis V. (1956), "On a Measure of the Information Provided by an Experiment," *Annals of Mathematical Statistics*, 27 (December), 986–1005.

Lund, Carsten and Mihalis Yannakakis (1994), "On the Hardness of Approximating Minimization Problems," *Journal of the Association for Computing Machinery*, 41 (5), 960–81.

Martignon, Laura and Ulrich Hoffrage (2002), "Fast, Frugal, and Fit: Simple Heuristics for Paired Comparisons," *Theory and Decision*, 52 (1), 29–71.

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 (2), 165–81.

Montgomery, H. and O. Svenson (1976), "On Decision Rules and Information Processing Strategies for Choices Among Multiattribute Alternatives," *Scandinavian Journal of Psychology*, 17 (4), 283–91.

Ofek, Elie and V. Srinivasan (2002), "How Much Does the Market Value an Improvement in a Product Attribute?" *Marketing Science*, 21 (Fall), 398–411.

Olshavsky, Richard W. and Franklin Acito (1980), "An Information Processing Probe into Conjoint Analysis," *Decision Sciences*, 11 (July), 451–70.

Ordóñez, Lisa D., Lehmann Benson III, and Lee Roy Beach (1999), "Testing the Compatibility Test: How Instructions, Accountability, and Anticipated Regret Affect Prechoice Screening of Options," *Organizational Behavior and Human Decision Processes*, 78 (April), 63–80.

Payne, John W. (1976), "Task Complexity and Contingent Processing in Decision Making: An Information Search," *Organizational Behavior and Human Performance*, 16 (August), 366–87.

———, James R. Bettman, and Eric J. Johnson (1988), "Adaptive Strategy Selection in Decision Making," *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 14 (3), 534–52.

———, ———, and ——— (1993), *The Adaptive Decision Maker*. Cambridge, UK: Cambridge University Press.

Perreault, William D., Jr., and Laurence E. Leigh (1989), "Reliability of Nominal Data Based on Qualitative Judgments," *Journal of Marketing Research*, 26 (May), 135–48.

Roberts, John H. and James M. Lattin (1991), "Development and Testing of a Model of Consideration Set Composition," *Journal of Marketing Research*, 28 (November), 429–40.

Rossi, Peter E. and Greg M. Allenby (2003), "Bayesian Statistics and Marketing," *Marketing Science*, 22 (3), 304–328.

Shao, Jun (1993), "Linear Model Selection by Cross-Validation," *Journal of the American Statistical Association*, 88 (June), 486–94.

Shocker, Allan D., Moshe Ben-Akiva, Bruno Boccara, and Prakash Nedungadi (1991), "Consideration Set Influences on Consumer Decision-Making and Choice: Issues, Models, and Suggestions," *Marketing Letters*, 2 (3), 181–97.

Shugan, Steven (1980), "The Cost of Thinking," *Journal of Consumer Research*, 27 (2), 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*, 32 (August), 255–66.

Simon, Herbert A. (1955), "A Behavioral Model of Rational Choice," *Quarterly Journal of Economics*, 69 (1), 99–118.

Srinivasan, V. (1988), "A Conjunctive-Compensatory Approach to the Self-Explication of Multiattributed Preferences," *Decision Sciences*, 19 (2), 295–305.

——— and Chan Su Park (1997), "Surprising Robustness of the Self-Explicated Approach to Customer Preference Structure Measurement," *Journal of Marketing Research*, 34 (May), 286–91.

Swait, Joffre and Tülin Erdem (2007), "Brand Effects on Choice and Choice Set Formation Under Uncertainty," *Marketing Science*, 26 (September–October), 679–97.

Toubia, Olivier, Theodoros Evgeniou, and John Hauser (2007), "Optimization-Based and Machine-Learning Methods for Conjoint Analysis: Estimation and Question Design," in *Conjoint Measurement: Methods and Applications*, 4th ed., Anders Gustafsson, Andreas Herrmann, and Frank Huber, eds. New York: Springer, 231–58.

——— and John R. Hauser (2007), "On Managerial Efficient Designs," *Marketing Science*, 26 (November–December), 851–58.

Tversky, Amos (1972), "Elimination by Aspects: A Theory of Choice," *Psychological Review*, 79 (4), 281–99.

Urban, Glen L. and John R. Hauser (2004), "'Listening In' to Find and Explore New Combinations of Customer Needs," *Journal of Marketing*, 68 (April), 72–87.

Vapnik, Vladimir (1998), *Statistical Learning Theory*. New York: John Wiley & Sons.

Wu, Jianan and Arvind Rangaswamy (2003), "A Fuzzy Set Model of Search and Consideration with an Application to an Online Market," *Marketing Science*, 22 (3), 411–34.

Yee, Michael, Ely Dahan, John R. Hauser, and James Orlin (2007), "Greedoid-Based Noncompensatory Inference," *Marketing Science*, 26 (July–August), 532–49.

Zhang, Tong (2003), "Leave One Out Bounds for Kernel Methods," *Neural Computation*, 15 (6), 1397–1437.