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A marketing science perspective on recognition-based heuristics (and the fast-and-frugal paradigm)

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Abstract

Marketing science seeks to prescribe better marketing strategies (advertising, product development, pricing, etc.). To do so we rely on models of consumer decisions grounded in empirical observations. Field experience suggests that recognition-based heuristics help consumers to choose which brands to consider and purchase in frequently-purchased categories, but other heuristics are more relevant in durable-goods categories. Screening with recognition is a rational screening rule when advertising is a signal of product quality, when observing other consumers makes it easy to learn decision rules, and when firms react to engineering-design constraints by offering brands such that a high-level on one product feature implies a low level on another product feature. Experience with applications and field experiments suggests four fruitful research topics: deciding how to decide (endogeneity), learning decision rules by self-reflection, risk reduction, and the difference between utility functions and decision rules. These challenges also pose methodological cautions.

Keywords: consideration sets, ecological rationality, evaluation cost model, fast-and-frugal heuristics, self-reflection learning, non-compensatory decision rules, product development, recognition heuristic.

1 A marketing science perspective

Marketing science provides a valuable perspective on whether and why consumers use recognition-based heuristics.[1] This perspective is grounded by field experiments, the analysis of large data sets such as those obtained from supermarket-scanner panels, formal theory, prescriptive applications, and managerial experience. This perspective complements the theories and experiments in the fast-and-frugal paradigm.

Our perspective is shaped by trying to understand how real consumers in real markets make decisions, how consumers use information from the firm and other consumers, and how consumers learn about new products. As a field we've developed many prescriptive tools including laboratory test markets that predict sales to within two share points, prelaunch forecasting systems to understand the communications (advertising, word-of-mouth, salesforce, etc.) necessary to sell a target product, information acceleration to put consumers "into the future" to predict the acceptance of really-new products such as electric vehicles, websites that "morph" to better match consumers' cognitive styles, and preference/decision-rule elicitation methods that predict in-market behavior for redesigned products (Hauser, Tellis, and Griffin 2006, and references therein). All of these tools have at their core descriptive models of consumer behavior.

My colleagues in the field of marketing research and I have explored measurement systems including web-based questionnaires that adapt questions for maximal information, automated Bayesian systems that "listen in" on consumers who use online advisors, and a variety of qualitative experiential methods to understand the "voice of the customer". Most recently we've explored methods to estimate non-compensatory decision rules from observed choices (Dieckmann, Dippold, & Dietrich 2009; Hauser, Toubia, et al. 2010; Kohli & Jedidi 2007; Sawtooth Software 2008; Yee, et al. 2007). We've also explored direct elicitation. Consumers reveal their decision rules by teaching agents to buy in their stead. (For example, in a recent survey, respondents had a reasonable chance of receiving a $40,000 automobile where the specific vehicle they received depended upon their answers to the survey [Ding, et al., 2011].) Because our ultimate goal is to design and market new products, our focus has been in the field ("*in vivo*") rather than in the laboratory ("*in vitro*"). It is from this field experience that I comment upon recognition-based heuristics and related issues.

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[1] Gigerenzer and Goldstein (1996) discuss the recognition heuristic. I understand there are many debates as to the exact definition of the recognition heuristic, including how it is applies when consumers are unsure about cues and whether it applies when the cues are more than just brand names. To avoid that debate and focus on a marketing science perspective, I use the broader term, "recognition-based heuristics". I thank the editors for this suggestion.

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2 Ecological rationality

Almost 150 years ago an American president, Abraham Lincoln (attributed 1858), said, "You can fool some of the people all of the time, and all of the people some of the time, but you cannot fool all of the people all of the time." The analogy in product development is that some people will buy bad products and some people will be fooled by persuasive communications, but most of the time good products with good marketing will be successful and profitable. Firms that understand consumer needs and act responsibly on that knowledge tend to succeed disproportionately more than those who do not (e.g., Henard & Szymanski 2001; Montoya-Weiss & Calantone 1994). By implication, if we find consumers routinely using short cuts in their decision processes, then most of the time those shortcuts are probably pretty reasonable. When developing prescriptive tools, we often find shortcuts or heuristics to be good descriptors of consumer decision rules. I provide here a few of the many examples.

- When allocating their budgets to large purchases (automobiles, vacations, appliances) consumers use relatively simple rules (Hauser & Urban 1986). For example, the "value priority" rule states that consumers have in their mind a "utility" for the benefits of the purchase and rank budgeted items on utility divided by price. (Alternatively, the "net value priority" rule states they rank budgeted items on utility minus a constant times price. Empirically, the net-value priority rule predicts purchases slightly better, but not significantly so.) While these rules seem like heuristics, Hauser and Urban demonstrate that the rules solve the budget allocation problem optimally when products were infinitely divisible. The rules are close to optimal when products are discrete.

- When faced with many products from which to choose, most consumers use a consider-then-choose decision rule (Hauser & Wernerfelt 1990). Typically, observed consideration sets are often quite small relative to the number of brands on the market—about 10% of the available brands. Hauser and Wernerfelt argue further that a consider-then-choose rule is likely the optimal decision strategy when the consumer incurs evaluation costs. For example, if the consumer were to consider more brands he or she would incur a larger evaluation cost. Evaluation costs include both search and thinking costs (Shugan 1980). However, the net utility gained may not justify the additional evaluation cost. (The net utility is the benefit gained by consuming the best brand from the larger set minus the benefit gained from consuming the best brand from the smaller set. If brands are similar, this gain can be very small.) Data suggest that consumers are coming close to the optimal solution. Interestingly, the authors present evidence that firms themselves react optimally to the fact that consumers use a consider-then-choose process.

- When faced with many information sources such as dealer visits, word-of-mouth, advertising, and reviews (for automobiles), consumers allocate more time to those sources that cause them to change their choice probabilities more (Hauser, Urban, and Weinberg 1993). Consumers take into account whether the information is positive or negative with negative information having a larger impact per unit time. And consumers look ahead to the information they might obtain from another source, but they look ahead only one step. Overall, the observed search strategy is cognitively simple, but approximates well the optimal solution to a mathematical program in which consumers allocate their time among sources of information.

These observations of consumers making real choices suggest that simplified decision rules are ecologically rational. For the three examples, and others not listed, we observe consumers using decision rules that are simple, but the simple rules match optimal strategies. For example, in mathematical programming terms the value-priority algorithm is a "greedy algorithm" and it is the optimal solution to the budget allocation problem under reasonable conditions.[2] (The net-value priority algorithm is also an optimal solution to the budget allocation problem. This "dual" problem leads to the same optimal solution, but the process by which optimality is obtained is different.[3]) Real-world conditions do not always match the ideal conditions, but the algorithm is close to optimal for real-world conditions. The consumer loses very little in terms of utility by using the simple rules. But this is only part of why the decision rules are ecologically rational. We argue below that consumers can expect firms to take the simple rules into account when they develop and promote their products. This leads to a world where the consumer can be confident that firms will provide an environment in which the simplified decision rules give close to optimal results.

[2]The algorithm is called greedy because it operates myopically by choosing the object that gives it the most "bang for the buck", in this case, the largest value of "utility per unit of price". Greedy algorithms represent an important and well-studied class of mathematical programs (Edmonds, 1971).

[3]Duality theory is beyond the scope of this commentary (Walk, 1989). In mathematical programming many problems have dual problems. The solution to the dual problem is the same as the solution to the original problem (called the "primal"). However, the process used to obtain the solutions to the two related problems might be different. Sometimes it is easier to solve the related problem (the "dual") rather than the original problem.

Observed consumer behavior can be ecologically rational if consumers' decision rules are close to utility-maximizing because they "exploit structures of information in the environment (Goldstein & Gigerenzer 2002, p. 75)". The three conditions set forth by Gigerenzer and Goldstein (2011, p. 104) help us identify those situations where the recognition-based heuristics are close to the optimal *consumer* decision rule. Gigerenzer and Goldstein suggest that we should observe consumers using the recognition heuristic when (1) recognition distinguishes well-perceived brands from poorly-perceived brands—a substantial recognition validity above 0.5, (2) recognition is relevant to the product category (reference class) in which the consumer is making a decision, and (3) the products being evaluated are representative of the reference class.

Based on these results and the rich literature in judgment and decision making, the next section explores when we might expect to see the recognition-based heuristics as a partial explanation of consumer decision making in real markets (*in vivo*). The following section explores characteristics of consumer decision making to suggest fertile areas of research on recognition-based heuristics and, more generally, on the fast-and-frugal adaptive toolbox.

3 Recognition-based heuristics in marketing science applications

3.1 New product forecasting

New product forecasting models for frequently-purchased products (deodorants, laundry detergents, juice drinks, etc.) incorporate a construct that is related to recognition. The construct is awareness. Specifically, let a_w be the percent of consumers aware of the new product, a_v be the percent of consumers who will find the new product available in the stores or on the web, T be the percent of consumers who will try the new product (conditioned upon awareness and availability), and R be the probability of becoming a repeat consumer (conditioned upon trial).[4] Then, to a first order, the market share of a new product is given by:[5]

$$share = a_w a_v TR \tag{1}$$

In frequently-purchased categories, consumers repurchase often, so a product cannot succeed if it does not satisfy consumer needs—if it does not earn R. But it also cannot succeed if it is never considered—if it does not earn a_w and T. (For this paper we ignore availability, a_w.[6])

In marketing two awareness constructs are measured and used in managerial decision making: unaided awareness and aided awareness. Unaided awareness is a more stringent criterion than aided awareness. For example, try to recall without aids the brands of deodorants on the market. When I ask MBA students to name deodorant brands (unaided awareness), each student can rarely name more than three brands. However, when I read a list of brands (aided awareness), the same students can easily recognize twenty or more brands. Unaided awareness is an excellent predictor of the brand the consumer will consider (Silk & Urban 1978; Urban & Katz 1983), and brand consideration is an excellent predictor of brand choice.[7] For example, in one study consideration explains approximately 80% of the uncertainty in deodorant choice (Hauser, 1978).[8]

In marketing contexts it is important to distinguish whether consumers recognize brands with or without cues. If a consumer is given two or more brands and asked to choose among them, he or she is likely to use recognition as a first screen. If the choice is made in the laboratory, recognition is based on aided awareness because the consumer is given the brands to choose among.

[4]For frequently-purchased products the firm's profit depends upon a sustained level of purchasing among consumers. A consumer may try a product (trial) for many reasons including free samples, but unless trial leads to repeat purchasing (repeat) the new product is not profitable. For example, overly persuasive advertising might encourage many consumers to try a new deodorant. However, if those consumers try the deodorant and find it does not live up to the advertising they may not repeat their purchase and the deodorant's long-term sales will decline. On the other hand, if a product is really great a firm might "buy" trial with free samples. It loses money on the first purchase but more than makes that up on subsequent repeat purchases.

[5]In practice, forecasts often take into account how the consumer became aware of and/or tried the product. For example, there may be self-selection on advertising-based trial that is different than self-selection on trial based on receiving a free sample (e.g., Shocker & Hall 1986). These additional complexities have practical importance, but do not change the conceptual arguments in this commentary.

[6]It is beyond the scope of this commentary, but retailer's decisions to carry a product depend up the ability of the product to gain awareness, trial, and repeat. Similarly, the manufacturer's willingness to spend on gaining shelf facings or other distribution is dependent upon the ultimate sales potential of the new product.

[7]The detailed definition of "consideration" varies in marketing science. The basic definition of consideration is that the consumer will seriously evaluate the brand for potential purchase or consumption. For example, to consider a deodorant the consumer must expend cognitive and other resources to evaluate the deodorant for his or her use. This may mean reading the label, talking to friends, attending to advertising, sampling the fragrance, imaging the use of the deodorant, etc. For frequently-purchased products consumers may alternate purchases of considered products because together the portfolio of products serve their needs across consumption situations. They might have one deodorant for everyday use, one for sports, and one for special social occasions.

[8]While these citations are over thirty years old, these relationships still hold today and are used to forecast the success, or lack thereof, of new frequently-purchased products.

On the other hand, in real markets the consumer might make a shopping list or ask an agent to buy (spouse, parent, roommate, etc.). The consumer might even look through shelf facings in the supermarket or drug store and choose to examine those brands most recognizable. Shopping lists are likely based on unaided awareness, shelf-facing examination is likely based on a hybrid of aided and unaided awareness.

In laboratory test markets (also called "simulated test markets"), consumers complete tasks that provide estimates of T. Repurchase, R, is measured post laboratory. Brand plans for advertising and other communications provide data with which to estimate a_w. While practice is not univocal, it is more likely that awareness is an analog that is related to recognition. Real managerial decisions, and possibly millions of dollars in brand communications, are based on the goal of achieving aided and unaided awareness. For example, Proctor and Gamble spent \$5.2 billion in 2008 on advertising and Unilever spent \$7.8 billion in 2007.[9]

While we argue below that recognition analogs are not the only decision rules used by consumers, simple recognition-based decision rules are clearly applicable in frequently-purchased product categories. In non-frequently-purchased product categories, such as consumer durable goods (automobiles, computers, furniture, appliances), recognition may be a screening rule but, before choosing a product, consumers are more likely to seriously evaluate those brands that are not screened out. In durable goods the (initial) purchase is relatively more important to consumers than repeat purchases which may occur years hence rather than weekly or monthly. Such variation in relevancy is consistent with the adaptive-toolbox paradigm. Consumers use recognition-based heuristics when such heuristics are likely to help consumers make good decisions. They use other decision rules in other situations.

3.2 Are recognition-based heuristics ecologically rational in brand choice?

We have argued that consumers use recognition as a screening rule, but, for recognition-based screening to be ecologically rational, the information in the environment should be such that consumers can exploit recognition to make better decisions. Simple heuristics often serve consumers well (Marewski, Gaissmaier, & Gigerenzer 2010). Some theories in marketing science suggest why consumers can rely on simple heuristics.

One theory of advertising, called "burning money in public", is a signaling theory. Advertising is ephemeral; once money is spent there is no salvage value. Clearly a large advertising campaign (including web-based and social-media advertising) causes consumers to become aware, but it might also be rational for consumers to infer quality from the advertising campaign. The theories themselves are based on formal game theory and are carefully developed (e.g., Milgrom & Roberts 1986, Nelson 1974; Erdem & Swait 1998),[10] but the basic intuition is simple. A brand will succeed if it is sufficiently high quality to earn repeat purchases (R in Equation 1). If the firm advertises the brand and consumers try the brand, the firm can recoup its advertising expenditures through repeat purchase. On the other hand, if the brand is low quality it cannot recoup its advertising expenditures and will choose not to advertise. Through experience, consumers learn that heavily advertised brands are high quality and infer from advertising alone that the brand is high quality. It is only a small step from these signaling theories to recognition-based heuristics. Because advertising causes awareness of the brand name, and awareness is an analog of recognition, the consumer can infer high quality from recognition.

Even without game theory, we can see intuitively that firms with high quality brands will advertise more (and that it is rational for consumers to use recognition-based heuristics). In a simple model, profit (π) is equal to the margin, m, from a sale times the sales volume, minus the cost of advertising (A). We continue to use the model of Equation 1 in which *share* is equal to awareness (a_w) times availability (a_v) times trial (T) times repeat (R). If there is a fixed volume, V, in the market, this abstract model gives us:[11]

$$\pi = mV * share - A = mVa_w a_v TR - A \qquad (2)$$

It is reasonable that there are decreasing marginal returns to advertising spending.[12] If advertising only affects awareness, then decreasing marginal returns implies that $a_w(A)$ is concave in A. (By concave we mean the second derivative of a_w with respect to A is negative.) We maximize profit by setting the derivative of π equal to zero and

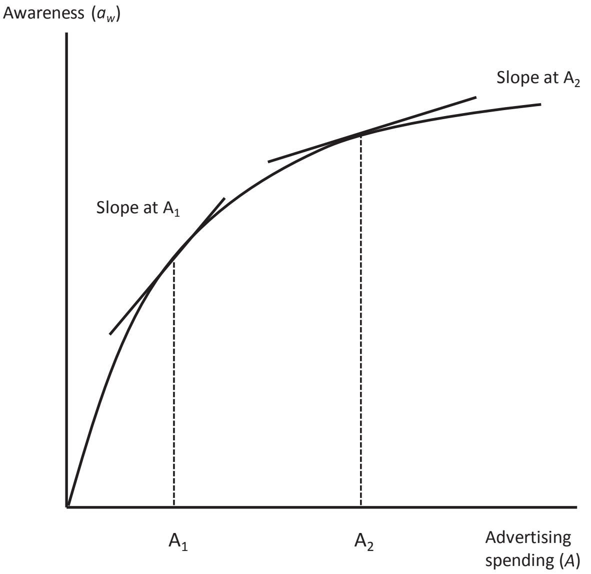
[9] http://www.bnet.com/blog/advertising/jim-stengal-proctor-and-gambles-global-marketing-chief-stepping-down/148. http://www.marketingvox.com/more-new-media-less-tv-for-kimberly-clark-and-unilever-036879/.

[10] The basic idea is that there is a "separating equilibrium" in which it is rational for the high-quality firm to advertise heavily and it is not rational for the low-quality firm to advertise heavily. In addition, it is rational for consumers to rely upon the advertising as a signal of high quality. Milgrom and Roberts expand on Nelson's ideas to demonstrate that signaling is complicated by the fact that price can also be used as a signal. But the basic intuition survives.

[11] Fixed volume is sufficient but not necessary. I assume fixed volume to simplify exposition.

[12] Some static advertising response functions are S-shaped. However, even with S-shaped curves, it is optimal for the firm to operate on the concave portion of the curve or to operate at zero advertising (Little, 1979).

Figure 1: Concave Advertising Response Curve Implies More Advertising Spending for Higher-Quality Products.



solving for A. In symbols:

$$\frac{\partial \pi}{\partial A} = mVa_vTR\frac{\partial a_w}{\partial A} - 1 = 0,$$

which implies

$$\frac{\partial a_w}{\partial A} = \frac{1}{mVa_vTR} \quad (3)$$

If the higher quality brand gets a higher trial and/or repeat, then TR is larger. Equation 3 implies that it is optimal for the firm to set A such that $\partial a_w/\partial A$ is smaller because it must equal $1/mVa_vTR$, which is smaller when TR is larger. This condition implies that optimal advertising for a high-quality product (vs. a low-quality product) occurs where the $a_w(A)$ curve is flatter. A concave curve is flatter when A is larger. Figure 1 provides a visual perspective of the implications of Equation 3. The slope of $a_w(A_2)$ is lower than the slope of $a_w(A_1)$ because higher quality implies that $1/mVa_vT_2R_2$ is lower than $1/mVa_vT_1R_1$. The first-order conditions in Equation 3 can be satisfied only if A_2 is greater than A_1. In other words, the higher quality brand will advertise more and the consumer can infer quality from recognition.

Learning by observing other consumers (observational learning) reinforces recognition as a rational screening mechanism. Specifically, if many other consumers use a product, then a consumer might infer that the product is of high quality. But if many other consumers use a product, then it is more likely that the consumer will see the product being used. This usage will lead to recognition. Following this chain backwards the consumer might then infer that products are recognized if and only if they are higher quality. This argument is related to the "criterion ↔ mediator ↔ name-recognition" triangle in Marewski, et al. (2010) by substituting observational learning for media mentions.

Observational learning is common among consumers and affects their behavior. For example, Tucker and Zhang (2010, 2011) describe field experiments in which consumers use information on popularity to choose which websites to visit. Zhang (2010) demonstrates that organ recipients infer quality from prior rejections and it is rational for them to do so.

Many websites, such as Amazon.com, use collaborative filters to recommend products (Breese, Heckerman, & Kadie 1998). For example, if I were to purchase *Gut Feelings* by Gerd Gigerenzer, Amazon.com would recommend other books that "customers who bought this item also bought". If social networks are such that the consumers I observe most often share my preferences, then it is rational for consumers to rely on observation of their friends and acquaintances to infer which products match their preferences. Such inferences are enhanced when practical or economic constraints limit the feasible combinations of aspects that a brand can offer. (Following Tversky [1972], an aspect is a characteristic of the brand, such as, "cleans cottons effectively".)

For example, a laundry detergent that cleans white cotton fabrics well might be less gentle to delicate fabrics. With constraints on the ability to offer aspects, in equilibrium, firms will offer products that are on the "efficient frontier". (By efficient frontier we mean that no viable brand is dominated by another brand as long as price is considered an aspect of the brand.) When all brands are on the efficient frontier, the consumer need only decide if the brand matches the tradeoffs among aspects that he or she wishes to make. For example, if there were only two aspects that described laundry detergents, "gentleness" and "effectiveness", then I can choose the laundry detergent that is best for me by only considering "effectiveness". I can do this because, among efficient-frontier products, the negative correlation of "gentleness" and "effectiveness" enables me to infer the "gentleness" of a detergent from the detergent's "effectiveness". Finally, if my friends and acquaintances share my preference tradeoffs, the laundry-detergent brand that they most prefer may be the laundry-detergent brand that I would most prefer. I am most likely to prefer the brand that I recognize because my friends and acquaintances use that brand.

Research on consumer decision rules is consistent with the efficient-frontier story. Non-compensatory heuristics often predict consumer preferences better than linear (compensatory) models in environments where aspects are negatively correlated as they would be if all brands

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were on the efficient frontier (Johnson, Meyer & Ghose 1989).[13]

3.3 Sometimes recognition is only part of the overall story

Brand consideration is managerially important in the automotive industry. For example, a major US automotive manufacturer ("USAM") invested substantial resources to study how they might entice consumers to consider their automobiles. Based in part on consumer experiences with past vehicles, one-half to two-thirds of US consumers would not consider USAM's brands. Even though USAM had excellent new vehicles as judged by independent ratings, this lack of consideration meant that consumers would not observe that improved quality. After testing a variety of strategies, USAM determined that focused competitive test drives and putting unbiased competitive brochures on their website would enhance trust which, in turn, would enhance consideration (Liberali, Urban & Hauser 2011). For example, competitive test drives were projected to increase consideration by 20% if implemented nationally. Strategies such as unbiased online advisors and community forums did not enhance consideration. Although they might have signaled trust, they also communicated aspects of USAM's past vehicles that were of lower quality. USAM's field experiments suggested that USAM needed strategies that did more than increase brand recognition; USAM needed marketing strategies that made it cost-effective for the consumer to obtain the information needed to evaluate a USAM brand.

Using extensive qualitative interviews, USAM came to understand that the majority of consumers (76%) were making consideration decisions based on non-compensatory heuristics—not recognition alone but rather conjunctions (and disjunctions of conjunctions) of aspects. To design vehicles and to design marketing campaigns based on consumer decision rules, USAM invested substantial resources to identify the heuristic decision rules consumers use when deciding whether to consider brands. In a decision problem with 53 aspects, non-compensatory models proved to be a much better description of consumers' decision rules than additive models (Dzyabura & Hauser, 2011). USAM used these data to identify clusters of consumers who share decision heuristics. That is, consumers were clustered based on the aspects that they used in their decision rules and whether they used a conjunctive or a compensatory decision rule. The main clusters were (1) conjunctive using primarily brand and body-type aspects, (2) conjunctive using brand aspects, (3) conjunctive using body-type aspects, and (4) compensatory using a larger number of aspects.[14] Consumers in these clusters also used other automotive aspects in either their conjunctions or compensatory rules. In automotive markets, recognition of a brand *and its aspects* serves as a cue and consumers infer quality from advertising and from observing other consumers, but consideration is more than recognition. Almost all consumers recognize USAM's brands (even unaided); the majority of consumers would just not consider USAM's brands. In order to move from recognition to consideration (and then to purchase), consumers need more-detailed information about the aspects of USAM's brands—information such as body type, quality, crash-test ratings, fuel mileage, ride and handling, style, and other features. Rather than using recognition alone, consumers use heuristic decision rules based on these aspects to screen brands, typically to less than 10% of the brands on the market (Hauser & Wernerfelt, 1990).

The difference in the use of recognition-based heuristics between frequently-purchased products and automotive products is due, in part, to the magnitude of the consumer's decision. Purchasing a vehicle is one of the most significant consumer decisions. Consumers might eliminate a few brands because the consumer does not recognize the brands (e.g., Tata), but it is rare that recognition will be part of the heuristic decision rule. Using decision rules with more aspects is rational in automotive decisions even though search costs are substantial (visiting a dealer, searching the Internet, talking to other consumers, paying close attention to advertising, etc.). For example, a consumer who wants to consider all sporty luxury coupes may begin his or her search for a new automobile by actively seeking to learn which brands have sporty luxury coupes.

3.4 Evaluation-cost model of brand consideration

The evaluation-cost model of brand consideration provides insight into how consumers might match heuristic decision rules to problems. Let $\tilde{u}_j$ be the consumer's beliefs about the utility of the j^{th} brand. The tilde (˜) over the $\tilde{u}_j$ indicates that, prior to second-stage evaluation, the consumer is uncertain about the utility he or she will re-

[13] Prediction is not the same as explanation. However, if the use of decision rule A predicts consideration or choices better than the use of decision rule B it is partial evidence that decision rule A is a better explanation of consumer decisions than decision rule B. This is especially true for out-of-sample predictions that are delayed or which are tested on different sets of product profiles. (A profile is a hypothetical product described by its aspects.)

[14] Brands included BMW, Buick, Cadillac, Chevrolet, Chrysler, Dodge, Ford, GMC, Honda, Hyundai, Jeep, Kia, Lexus, Lincoln, Mazda, Nissan, Pontiac, Saturn, Subaru, Toyota, and Volkswagen. Body types included sports car, hatchback, compact sedan, standard sedan, crossover vehicle, small SUV, full-sized SUV, pickup truck, and mini-van.

ceive from the j^{th} brand. Let s_j be the search cost for the j^{th} brand. We've assumed that the consumer knows the search cost, but allowing search cost to be a random variable does not change the basic argument. Then, in a sequential search, it is rational for the consumer to consider the n + 1^{st} brand if:[15]

$$\max_{\mathrm{j=1\ to\ n+1}} E\{\tilde{u}_1, \tilde{u}_2, \ldots,\ \tilde{u}_n, \tilde{u}_{n+1}\} - \max_{\mathrm{j=1\ to\ n}} E\{\tilde{u}_1, \tilde{u}_2, \ldots,\ \tilde{u}_n\} > s_{n+1} \quad (4)$$

That is, if the consumer could anticipate the maximum values, the consumer would compare the expected return from choosing the best from n + 1 brands to the expected return from choosing the best from n brands. If that increment is larger than the search cost, the consumer will consider the n + 1^{st} brand; if not, stop. Even if all brands had the same expected utility, it is easy to show that the left-hand side of Equation 4 is decreasing in n. If the consumer uses an heuristic so that earlier-searched brands have larger expected values, the decrease is exacerbated.

Equation 4 implies conditions where we expect recognition-based heuristics to be rational for brand consideration. Let *m* be the number of recognized brands. Recognition-based heuristics will be rational for consideration if the search cost of an unrecognized brand is larger than the expected utility that might be gained if the consumer were to choose from the *m* recognized brands plus an additional unrecognized brand rather than if the consumer were to choose from only the *m* recognized brands. It is not unreasonable that this condition holds for deodorants: the expected increment from choosing (long term) from a slightly larger consideration set, say four deodorants, is likely to be small. The search cost, while not large, is not inconsequential. The consumer has to purchase the deodorant and try it, perhaps in odor-critical situations. If some of the conditions discussed earlier hold (advertising as signaling, observational learning, assumption of an efficient frontier among a relatively few brand aspects), then the consumer might stop after considering the brands that he or she recognizes.

In automotive decisions the search cost is much larger, but so are the differences in expected utility. Automotive brands vary on a large number of aspects and the consumer may need a larger consideration set to be comfortable about having enough exemplars of key brand aspects. Adding another brand to the consideration set might make new aspects available (all wheel drive, adaptive cruise control, city-safety-auto-stop, etc.). The value of choosing from a consideration set with an additional considered vehicle can be quite substantial. In many situations this increment in value exceeds the search cost the consumer incurs when he or she does not know the aspects of the unfamiliar brand. (Consumers may have mere brand-name recognition, say of Hyundai, but have little knowledge of Hyundai's aspects.)

Ding et al. (2011) summarize qualitative research by describing a consumer who they call "Maria". Maria used a conjunctive decision rule based on nine aspects to select her consideration set: sporty coupes with a sunroof, not black, white or silver, stylish, well-handling, moderate fuel economy, and moderately priced. Maria was typical. Ding, et al. used an incentive compatible task in which over 200 consumers described their decision rules. Most decision rules were simple and most rules had a non-compensatory component, but not a single consumer used brand recognition.

Automotive decision rules are best for the situation in which the consumers are asked to consider or choose a vehicle. Consistent with the paradigm of an adaptive toolbox, consumers might rely on recognition when selecting which deodorants to consider but rely on a many-aspect decision rule when selecting which automotive brands to consider.

3.5 Summary of marketing science experience

In real markets recognition-based heuristics can be ecologically rational. They are more likely rational and more likely to be observed as decision rules for products that are low cost and do not vary on many aspects. They are less likely to be used for products that represent a substantial purchase decision and which vary on many aspects. Consumers are likely to adjust their decision rules accordingly and managers can use the knowledge of such adaptation to design and market products more successfully.

4 Challenges

We return to theory and use marketing science experience to suggest fruitful areas of inquiry for research on recognition-based heuristics. I discuss four topics: endogenous search, learning by self-reflection, risk reduction, and the distinction between utility and decision rules. Each topic has been anticipated to some extent

[15] Although Equation 4 looks, at first glance, similar to "optimization under constraints" as used by Todd and Gigerenzer (2000, p. 729), it differs both technically and philosophically. Technically, we assume that the consumer solves this problem sequentially to decide which brands to evaluate further (consider). Empirically consumers consider roughly 10% of the brands on the market (Hauser and Wernerfelt 1990), so roughly 90% of the brands are never fully evaluated. Philosophically, Equation 4 is consistent with heuristic solutions to compute either of the maximizations, to decide which brands are eligible to be considered, or to approximate search costs. Equation 4 works perfectly fine as a paramorphic ("as if") description of consideration decisions rather than a process description.

in papers in experimental literature: Bröder and Newell (2008) discuss the impact of search. Betsch, et al. (2001) suggest that subjects learn enduring decision rules better with greater repetition. Bröder and Schiffer (2006) discuss risk taking. And, Gigerenzer and Goldstein (2011, p. 101) discuss the difference between "preferences and inferences". I believe that each topic is worth reviewing because each topic represents key differences between marketing applications and the typical laboratory tasks in the literature.

4.1 Search is endogenous

Automotive purchase decisions illustrate that the magnitude and complexity (number of aspects) of a decision affect the heuristic that consumers use. In real markets consumers can choose either to continue to search or to make a purchase decision with no additional search. Said another way, choosing to use recognition-based heuristics as evaluative decision rules is itself a decision that depends upon the information structure of the problem. In marketing science terms, this makes the decision rule endogenous (choosing the decision rule is part of the decision problem) rather than exogenous (the selection of the decision rule is pre-determined or determined by variables outside the problem at hand). The information structure can influence the decision rule, hence firms can take actions to influence the decision rule. If we observe a consumer using a decision rule in a real market it might be that we are observing the end result of firms' optimal actions to influence a decision rule. For example, if we observe a consumer using a conjunctive decision rule based on brand and body-type aspects (only Audi, BMW, or Chrysler brands; only coupes or convertibles), then this might be the result of specific Audi, BMW, or Chrysler advertising or this might be the result of the way a salesperson presented information to the consumer. We must also evaluate whether the consumer will accept the decision rules implied by advertising or salesforce messages or whether the consumer will override those decision rules based on the consumer's own preferences and experience.

Endogeneity means we must study how the consumer decides how to decide. The consumer's decision rule is not automatic, although it may be a subconscious rule learned by prior experience or by analogy to other situations. Firms should expect to be able to manipulate the use of recognition-based heuristics (and other heuristics) by changing the rewards and costs of information search. USAM's field experiments were, in part, an attempt to change the search costs for critical information and, hence, change consumers' consideration decisions. Even in the laboratory, if search and thinking costs are minimized in an experiment or if we greatly enhance the relative rewards among brands, we might expect consumers to rely less on recognition.

4.2 In new situations consumers learn decision rules by self-reflection

Hauser, Dong, and Ding (2011) sought to test three common methods of eliciting decision rules. Because they wanted to randomize over potential order effects (for within-subjects tests), they rotated the order of the tasks. Although one task was consistently better at predicting consideration in a delayed validation, they also found a large order effect, which persisted even when validation data were collected one-to-three weeks after the decision-rule-elicitation tasks.

Each of the three elicitation tasks were challenging to the subjects. For example, one task required that subjects evaluate 30 profiles on over 50 aspects. However, if the subject performed an elicitation task after another elicitation task, the subsequent task was a much better predictor of the delayed validation task. Qualitative data suggested strongly that the first task caused subjects to think deeply about the decision problem and, in doing so, think deeply about their decision rules. For example one subject volunteered "As I went through (the tasks) and studied some of the features and started doing comparisons I realized what I actually preferred." When subjects got to the second and/or third elicitation tasks they used learned decision rules and continued to use the learned decision rules in the validation task one week later. The study was replicated with cellular telephones (with validation three weeks later), using a different experimental design. The cellular-telephone results also suggested that consumers learn by thinking deeply about their own preferences.

An hypothesis that consumers learn their decision rules through self-reflection is subtly different from an hypothesis that consumers' decision rules are constructed in response to task characteristics and are easily influenced by manipulations (Payne, Bettman, & Johnson 1992, 1993). Self-reflection learning suggests that naïve consumers do not carry around preferences (among aspects) or decision rules for categories in which they have not yet made a recent choice. Rather, when faced with a decision task in a new product category, consumers learn their own decision rules by attempting to use those decision rules in realistic choice situations. The hypothesis differs from the constructed-decision-rule hypothesis because, once the decision rules are learned, the decision rules are remarkably enduring. The learned decision rules become part of the adaptive toolbox.

The learning-by-self-reflection experiments also suggest an important methodological issue for experiments on consumer decision rules. Prior to the first elicitation task, all subjects completed an incentive-compatible warm-up task in which they evaluated ten realistic product profiles. This warm-up task was larger than the vast majority of warm-up tasks in the constructed-decision-rule literature. Perhaps key experimental outcomes in the constructed-decision-rule literature might be reversed if the experimenter first gave consumers warm-up tasks that are sufficient to enable self-reflection learning of preferences and decision rules.

Recognition-based heuristic experiments might also be sensitive to learning through self-reflection. It might turn out that recognition-based heuristics are used more often (or less often) when consumers are learning how to decide. Recognition-based heuristics might be used differently after consumers learn how to decide in a particular product category. For example, when a consumer first starts listening to a new genre of music, the consumer might purchase those songs which he or she most easily recognizes. However, as the consumer's library of music increases and the consumer gains more experience with that genre of music, he or she might use a more sophisticated decision rule.

4.3 Recognition reduces risk

Roberts and Urban (1988) study the process by which consumers learn about aspects of new products. They model explicitly how new information reduces risk and demonstrate that decision rules that take risk reduction into account explain consumer behavior better than decision rules that do not. To illustrate their model consider the well-known results for risk on a single product aspect. Assume for a moment that the consumer uses only one aspect in his or her decision rule. Anticipating a multi-aspect model and without loss of generality, we designate that aspect as the first aspect. Let $\tilde{x}_{1j}$ be the uncertain value of that aspect for the j^{th} brand. The tilde (˜) continues to denote a random variable. If we assume the consumer is risk averse with risk-aversion coefficient r and if we assume that $\tilde{x}_{1j}$ is normally distributed with mean $\bar{x}_{1j}$ and variance σ^2_{1j} then it is easy to show that the consumer will choose the brand with the largest "certainty equivalent (ce)", where:[16]

$$ce_{1j} = \bar{x}_{1j} - (r/2)\sigma^2_{1j} \quad (5)$$

Equation 5 suggests that the consumer will discount risky brands, where risky has been defined by the fact that the consumer does not know for certain the level of the aspect that he or she will actually experience if he or she chooses (or at least considers) brand j.[17] To the extent that recognized brands have more certain aspects (lower σ^2_{1j}), Equation 5 provides one more argument why it may be rational to weigh more heavily recognized brands.

With the right technical assumptions we can extend Equation 5 to the multi-aspect case. Doing so leads us to use ce_{kj} rather than x_{kj} for the k^{th} aspect when we describe how the consumer chooses among brands. If the decision rule is linear in the aspects, then risk implies that we discount those aspects about which the consumer is uncertain. If the consumer recognizes the brand (and there is no uncertainty in recognition), but the consumer is uncertain about all other aspects of the brand, then brand recognition will be relatively highly weighted in the linear rule. Risk reinforces the rationality arguments of Davis-Stober, Dana, and Budescu (2010).

4.4 Consumer utility is not the same as a decision rule

Equation 5 establishes a case where the consumer's utility is linear with one set of weights, but the consumer's decision rule is linear with a different set of weights.[18] We use the results of Davis-Stober et al. (2010) to establish another case with strong face validity. For most consumers, utility (net of price) for a new automobile is clearly decreasing in price. If a consumer could buy a 2011 Maybach 62S Landaulet for \$10,000, he or she would surely consider it (assuming that the consumer recognized the Maybach brand and knew even a little about it). However, as much as we might like to dream, the Landaulet is reserved for "a select few customers with exceptionally deep pockets".[19]

Despite the fact that the consumer's utility function is decreasing in price, it is still rational for the consumer to use price as a screening criterion. (I did so with the last vehicle I purchased.) It is rational because the desired tradeoffs in aspects in a vehicle are highly correlated with price. Price enters the decision rule differently than it enters the consumer's utility function. By using price as a conjunctive criterion, the consumer can save the substantial search costs that might be incurred by test driving lower- and higher-priced vehicles. The lower- and higher-priced vehicles are not considered because there is little chance that the consumer would find the right as-

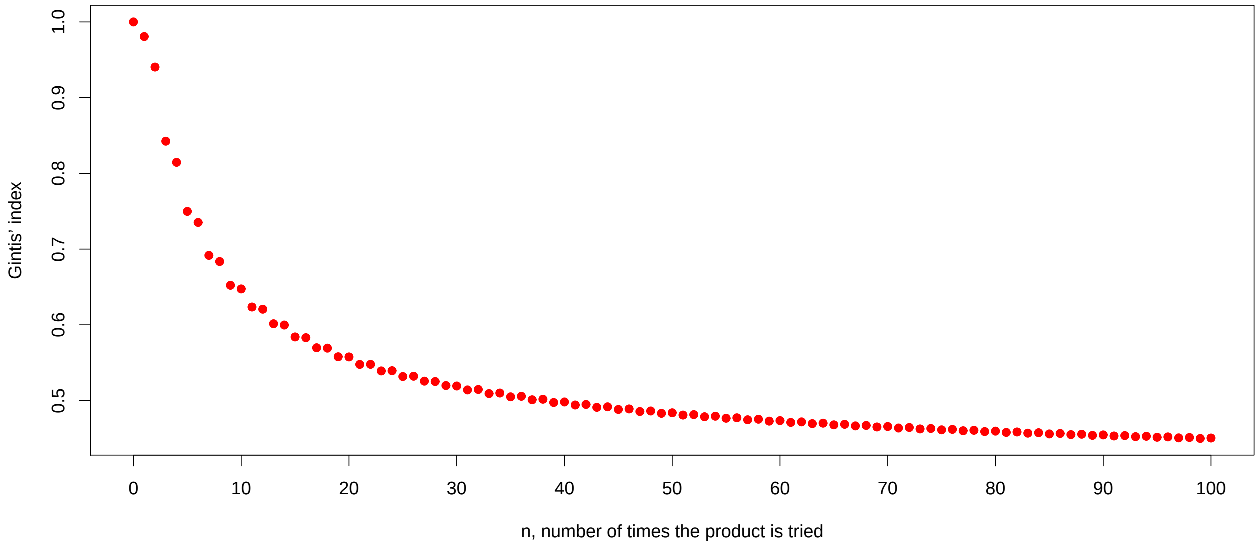
[16] A constantly risk-adverse utility function has the form $u(x_{1j}) = 1 - exp(-rx_{1j})$. To derive Equation 5 use the normal distribution to compute the expected utility over $\tilde{x}_{1j}$ and find the ce that makes the consumer indifferent between the certain reward of ce_{1j} and the uncertain reward of $\tilde{x}_{1j}$.

[17] Equation 5 is exact for the conditions stated, but likely a reasonable approximation for many utility functions and probability distributions. The basic concept of discounting for risk is more general.

[18] Hauser (2001) provides a managerial example in which R&D managers simplified a complex incentive problem to three metrics and then used an adaptable set of weights. The weights were set with a "thermostat" that optimizes profit rather than being based on managers' preferences.

[19] http://www.leftlanenews.com/maybach-62s-landaulet.html, visited February 2011.

Figure 2: Gittins' index as a function of the number of times the consumer tries a product.



pects in a lower-priced vehicle and little chance that the consumer would maximize his or her utility by choosing a higher-priced vehicle. Brand names, or even aspects such as "coupe", can easily enter a utility-maximizing consumer's decision rule in ways that differ from the ways the same aspects enter the consumer's utility function. This is particularly true of aspects that are negatively correlated with more-difficult-to-observe aspects that the consumer weighs heavily in his or her utility function.

My final observation is that some decision rules may be described by the researcher as heuristic simplifications but are actually optimal strategies by which the consumer can choose the product that maximizes utility. We have already seen that the value-priority algorithm for budget allocations and the more-time-for-higher-change-in-probability rule for information search are simple decision rules that might be described as heuristics but are, in fact, solution strategies that are near optimal. We expect to see such simple, but optimal, decision rules in other contexts.

For example, Gittins (1979) established the surprising result that the optimal solution to extremely-difficult infinite-horizon highly-uncertain decision problems has a simple form. The problem is known as the "multi-armed bandit" problem because of an analogy to slot machines in a casino. (Slot machines are known colloquially as one-armed bandits.) Suppose we are faced with N slot machines and want to win the most money. Each machine pays off with some probability and the probabilities vary. However, you don't know those probabilities. Each time you play a particular machine you learn something about its probability—you either win or not. The problem is to play the machines in some optimal manner trading off exploration (trying a new machine) with exploitation (playing the machine that you think has the highest probability of a payoff). This is an extremely difficult problem. Indeed, in an address to the Royal Statistical Society (February 14, 1979), the great statistician Peter Whittle opened: "[The bandit problem] was formulated during World War II, and efforts to solve it so sapped the energies and minds of Allied analysts that the suggestion was made that the problem be dropped [on their enemies], as the ultimate instrument of intellectual sabotage." When Gittins proved that the problem had a simple solution, he opened up an entire literature. Gittins' solutions now enable firms to solve all types of complicated choice problems including clinical trials, optimal experiments, job search, oil exploration, technology choice, and research & development project selection.

The proofs and the details are beyond the scope of this commentary. However, the basic form of the solution is to calculate an index for each choice object and, in every period, simply choose the object with the largest index. Subsequent research has shown that, while it may be difficult to compute the optimal index, indices can be approximated by simple functions. For example, consider Gittins' index for the multi-armed bandit described above, but replace product experience with slot machines. For illustration, abstract the problem so that consumers observe only that a product is of high quality of low quality. If n is the number of times the consumer experiences the product i and G_i is the Gittins' index, then $G_i(n)$ smoothly decreases in n as shown in Figure 2 (adapted from Hauser, et al. 2009, p. 221). In Gittins' solution each product has an index and the consumer always chooses the product with the highest index.

It is not at all unreasonable that consumers might intuit the function form of $G_i(n)$ and make close-to-optimal decisions with very simple rules. Consumers do not need to solve a complicated dynamic program to trade off learning about brands with consuming the highest-utility brand (Erdem & Keane 1996), but rather intuit a solution strategy that is somewhat similar to that described by an optimal Gittins' index.

In mathematical programming and in machine learning there are many algorithms that achieve close to optimality with simple decision rules. We might expect consumers to learn these simple rules by experience or by observing others. Machine learning uses the concept of "complexity control" to improve the performance of algorithms (e.g., Vapnik, 1998). The basic idea is to impose a constraint on the parameter space. This constraint, often arbitrary, prevents the algorithm from exploiting random error when choosing parameters. Subsequent predictions are more likely to be robust across situations that differ from the data on which they were calibrated. For example, Evgeniou, Pontil and Toubia (2007) use complexity control to improve the predictive ability of linear models used to forecast consumer response to new products.

The analogy for consumer decision making is cognitive simplicity. When we constrained estimation methods to enforce cognitive simplicity in decision rules, we found that we were able to predict consumer consideration decisions much more accurately (Hauser, Toubia, Evgeniou, Dzyabura and Befurt 2010).

5 Summary

Recognition-based heuristics, and fast-and-frugal heuristics in general, are relevant to marketing science. In many situations they are excellent descriptions of the decision rules that consumers use to consider brands and to choose brands. The insight gained from the study of these heuristics is valuable for the design and marketing of products.

Marketing science experience (*in vivo*) suggests that consumers use recognition-based heuristics or their analogs and do so in managerially relevant product categories. As we map the characteristics of the consumer's decision problem to situations where we expect heuristics to be close to optimal we gain insight on when we expect recognition-based heuristics to be used. The adaptive-toolbox paradigm helps us navigate these applications.

I hope that a marketing science perspective inspires research to understand further the adaptive toolbox hypothesis and recognition-based heuristics. Ideas and challenges that have proven valuable for prescriptive models confirm some findings and ask new questions. Although the problems addressed in marketing science may differ from the experimental literature and although the different fields often use different words to describe similar constructs, I hope we can learn from one another just as consumers learn decision rules in their ecologies.

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