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The authors assume consumers maximize value subject to a constraint on their time. The value of positive information is the increase in the expected utility of the consideration set; the value of negative information is the utility of choosing on the basis of the information versus the utility of a potentially erroneous decision without information. They examine four rules consumers use to select the order in which to visit sources. They use a multimedia computer laboratory, which allows consumers free choice among showroom visits, word-of-mouth interviews, magazine articles, and advertising for a new automobile. They estimate source value, compare predictions of time allocations to actual allocations, examine the impact of time constraints on the use of negative information, and calculate the relative performance of the source-order decision rules. They close with suggestions for experiments.

How Consumers Allocate Their Time When Searching for Information

The following example illustrates the problem we address. Monika has recently completed her dissertation and taken a faculty position at a prestigious university; Monika needs a car. Because she recognizes that there are over 300 makes and models on the market, she has already used a prescreening process to limit her consideration set to relatively few cars. But even so her task is formidable. Because this purchase may be the most expensive thus far in her life, she knows that her decision should be based on good information. But the demands of teaching and research imply that time spent searching for information will cost her dearly.

She can become well informed by reading *Consumer Reports, Car Driver, Road & Track,* and other magazines; she can seek the advice of friends, neighbors, and colleagues; and she can pay close attention to advertising. She can even visit a showroom, test-drive some cars, argue with a salesperson, and faint from sticker shock. But is it worth sacrificing her next research paper? From the perspective of consumer behavior theory, we want to know how she chooses among information sources and how the information affects her choice probabilities. From the perspective of an automobile manufacturer or dealer, we want to understand Monika's behavior so that we can invest in better communications to provide her with the information she needs to choose *our* car. From the perspective of a regulator we want to know how to provide information that will affect Monika's choice process. Naturally, we hope the theories of information search are not limited to automobiles but, for simplicity of exposition, we frame all examples and empirical data within the context of automobile choice.

We explore how she might allocate her time to alternative information sources and decide on the order in which to search these sources. For time allocation, we assume that Monika wishes to maximize the value she can obtain from the information sources within the constraints imposed by the rigors of her academic position. We recognize that sources can have value to Monika even when the information obtained does not favor the brand

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of automobile she is evaluating (negative information). For the order of selection of information sources, we consider models that vary from random choice to hyperrational choice. We indicate how one might estimate "value," make predictions about time allocations, and suggest how time constraints affect Monika's focus on positive versus negative information.

Data from an automotive prelaunch forecasting clinic provide an opportunity to explore time allocation and source order. This multimedia computer laboratory format allows consumers to access magazine articles, word-of-mouth interviews, and advertising, as well as "visit" a showroom and interact with a salesperson. We use the data to estimate the parameters of the model and use the parameters to make predictions of consumer time allocations. We compare our predictions to observed consumer time allocations, examine the impact of constraints, and make initial comparisons of different choice-of-source rules. We close with suggestions on how laboratory experiments might examine the models further.

WHICH, WHEN, AND HOW LONG?

Our theory attempts to explain how consumers allocate time among information sources. The general theory should apply whether the goal is to evaluate one brand or many, whether the consumer searches by brand (everything Monika can learn about the Mazda Miata) or by source (everything she can learn from *Consumer Reports*). With the technology currently available, we were limited to collecting data for the situation in which Monika searches sources that provide information on a specific brand. As multimedia technology advances multibrand laboratories will be feasible. We hope our theories and laboratory methods provide useful foundations to study time allocation and source order selection when consumers evaluate multiple brands.

Therefore, we frame our analyses within the context of information search for a specific brand of automobile, for example, the Miata. We assume that Monika is seeking information to decide whether to add that brand to her consideration set, and we allow that she may continue the search for other brands. The single-brand process may be repeated to a greater or lesser degree for all brands that pass Monika's prescreening process. As her consideration set evolves, some brands may be added and others deleted. We do not address the order in which Monika considers brands or whether she considers multiple brands simultaneously. However, if our theory fails for the special case of a single-brand search, it will likely fail for a multiple-brand search.

Even the search with respect to a single brand is complex. Monika must decide *which* sources to search—does *Consumer Reports* give enough information to justify the time commitment (and cost)? If a source is to be searched, Monika must decide *when* to search that source—should she read *Consumer Reports,* then go to the showroom, or should she go to the showroom, then read *Consumer Reports*? Once at a source, she must decide *how long* she should search it—when is long enough with a car salesperson? Naturally, all three decisions are interrelated. It may be worthwhile to read *Consumer Reports* before visiting a showroom but not after or visa versa. Or, the value of *Consumer Reports* (and hence whether it is worthwhile to read it) may depend on how much time Monika plans to spend (or actually spends) reading it. In this article, we begin with the "how much" decision by focusing on time allocation. The "which" decision is a decision to spend more than zero time on a source. We then address the "when" decision, that is, we consider the order in which Monika visits sources. Whenever feasible we discuss the relationships between time allocation and source order.

To examine these questions we use a rational cost/benefit framework. That is, we build our model on the basis of the concept that consumers seek benefits (value) from information and that these benefits must be balanced with the cost of obtaining that information. Our philosophy is that such a framework provides an approximation to consumer decision-making behavior while recognizing that the true process may be on the basis of more detailed, complex, and heuristic behavioral rules. Heuristic rules may have evolved and persisted because they are less taxing to the consumer's cognitive resources but lead to cost/benefit trade-offs that are "close" to optimal. See discussion and examples in Bettman (1979, proposition 5.3iiia), Copeland (1923), Hagerty and Aaker (1984), Hauser and Wernerfelt (1990), Irwin and Smith (1957), Juster and Stafford (1991), Lanzetta and Kanareff (1962), Marshak (1954), Meyer (1982), Painton and Gentry (1985), Punj and Staelin (1983), Ratchford (1982), Simonson, Huber, and Payne (1988), Swan (1969, 1972), and Urbany (1986). Payne (1982) compares cost/benefit models to "production-system" and "perceptual" viewpoints.

Cost/benefit models should provide a framework to explain aggregate phenomena parsimoniously and provide a basis with which other models can be compared. When appropriate cost/benefit models can be expanded to explore deviations from "rationality" or can be elaborated to explore less aggregate data. We begin with the time-allocation decision.

THE ALLOCATION OF TIME

To model Monika's time-allocation problem we define t_s as the time spent in source s and v_s as the value obtained from source s. The value may depend on t_s. We define a value function, $v_o(t_o)$, to represent the value of time spent on activities other than searching for information. That is, Monika gets $v_o(t_o)$ units of value for every t_o minutes spent on activities (research, teaching, etc.) other than shopping for an auto. In this formulation Monika has some budget, T, of available time; she must decide how much to allocate for information search (t_s's) and how much is left for other activities (t_o). For example, after working all week on teaching and administrative duties, Monika must decide how to spend her weekend. She could spend the entire weekend polishing her new paper on bilingual families or she could spend the entire weekend visiting Mazda dealers. More likely, she is willing to spend part of the weekend on research and part of the weekend at car dealers. Her decision depends on the value of the research (to her), v_o, the value of learning about the Miata from various sources, v_s's, and the time she allocates to the tasks, t_o and t_s's.

Equation 1 formalizes Monika's decision as maximizing value subject to a budget constraint.

$$\text{(1)} \qquad \max \sum_{s=1}^{S} v_s(t_s) + v_o(t_o)$$
$$\textit{subject to:} \sum_{s=1}^{S} t_s + t_o = T$$

One way for Monika to address the problem is to allocate her time at the beginning of the weekend, in essence budgeting time among visiting dealers and working on her research. Another way for Monika to address the problem is to visit the Mazda dealer and decide while talking to the salesperson when to leave. In reality, Monika probably does a little of both. In this section we assume that somehow, on the basis of her prior expectations, Monika knows which sources are worth considering, that she "visits" those sources, and that she leaves the sources when she realizes that any further time allocated to a source is no longer justified. We also assume decreasing marginal returns beyond an initial threshold. For example, we assume that Monika gets more information in the first hour at the dealer than she does in the second.

The distinction of whether we model the decision to go to a source and/or the decision to leave a source is important. Both are interesting and challenging problems. In the decision to go to a source we must know *before Monika goes to a source* Monika's expectations about the value she will obtain. In the decision to exit a source, we must observe (or model) the value Monika realizes from a source, but we can assume Monika computes this (marginal) value as she receives information from the source. We observe the value *after she exits the source* because time allocation focuses primarily on the exit decision.

Optimality Conditions

Equation 1 is a separable concave optimization problem.[1] Its solution is simple. For each source,

$$\text{(2)} \qquad \text{Either } t_s = 0$$
$$\textit{or}$$
$$\frac{\partial v_s}{\partial t_s} = \text{constant for all } s$$
$$\text{where constant} \geq V_o = \text{marginal value of free time.}$$

In words, if the value of a source is so low that its marginal value never exceeds that of free time, Monika will not search the source. Otherwise Monika allocates time to the source as long as she gets more value from the source than from spending time elsewhere. For example, Monika may intuit that one hour at a Mazda dealer is justified, but while she is at the dealer she might decide that her research time is more precious to her than spending the second hour at the same dealer. She may feel that watching television in the hope of seeing a Miata advertisement is not justified in terms of marginal value and, hence, allocate no time to TV.

When we choose a functional form for $v_s(t_s)$ and estimate its parameters, the optimality conditions in equation 2 predict consumer time allocations. We compare these predictions to actual time allocations in a later section.

Costs Other than Time

Though Monika may obtain *Consumer Reports* from her university's library, she might find it more convenient to purchase it at a newsstand. When she visits a dealer she has to pay transportation costs (bus fare or gas). In general, we model costs other than time by either (1) defining the value function to represent value net of costs (value minus monetary costs) or (2) by adding a monetary budget constraint to equation 1. Cognitive costs are implicit in the definition of value. For our data the consumers incurred no monetary costs, hence either formulation is consistent with our arguments. However, future papers may need to model such costs explicitly.

History

Suppose that Monika reads *Consumer Reports* and talks to her colleagues prior to her weekend outing to a Mazda dealer(s). The marginal value of the information that she obtains from the dealer may be less (or more) than she would have obtained had she not done her homework. This makes her decision process even more complex. The value of a source, say the dealer, depends on the other sources she searches prior to searching that source. Therefore, when we estimate our model, we allow the value function to depend on "history," that is, on the sources that have already been visited. We indicate the dependence on history with a subscript h. Naturally, to implement our model we represent $v_{sh}(t_s)$ by a parameterized function and estimate the parameters on the basis of observed search behavior.

THE VALUE OF INFORMATION

The Value of Positive Information

Suppose Monika is evaluating the Miata and focuses on a single source, s. With information Monika will likely

[1]Ratchford (1982) formulates a similar, but subtly different, model. He assumes that Monika minimizes welfare loss, that is, the value of the best alternative minus the value of the chosen alternative plus the search cost. In our model, Monika need not know the value of the best alternative. However, if we combine Ratchford's equations 9 and 11 with the assumption that the true value of the best alternative does not depend on the information obtained, then we obtain the same optimality conditions as equation 2. In equation 2, the constant equals V_o when t_o is non-zero.

update her beliefs about the Miata and, possibly, other cars that she is considering. Neither Monika nor we know yet whether she will ultimately choose the Miata. However, if the information about the Miata is positive, that is, if it makes the Miata a more attractive alternative and does not impugn other brands, then the value of Monika's consideration set is likely to increase because all alternatives are at least as good as before. In this case we model the value of the information from source s as the increase in the value of Monika's consideration set. That is, the value of source s equals the value that Monika expects to get by choosing from her consideration set *after* she knows the information in source s *minus* the value that Monika expected to get by choosing from her consideration set *before* she knew the information in source s.

A natural way to define the value choosing from a consideration set is by the expected value of the maximum utility obtainable from the consideration set (see Hauser and Wernerfelt 1990, equation 4, or Roberts and Lattin 1991).

To state this concept mathematically, let $\tilde{u}_{js}$, a random variable, represent Monika's beliefs about the utility of car j after searching source s, and let $\tilde{u}_{j\cdot}$, also a random variable, represent Monika's beliefs about the utility of car j before searching source s. Define $E_s[\cdot]$ as the expected value on the basis of information after source s has been searched and define $E.[\cdot]$ as the expected value before choosing a source to search. For positive information, the value, v_s, of searching source s is then

$$(3) \qquad v_s = E_s[\max(\tilde{u}_{1s}, \ldots, \tilde{u}_{js}, \ldots, \tilde{u}_{ns})] - E.[\max(\tilde{u}_{1\cdot}, \ldots, \tilde{u}_{j\cdot}, \ldots, \tilde{u}_{n\cdot})].$$

In the time-allocation decision, the value of the source is defined on the basis of the information the consumer actually obtains. When we address the source-order decision we must consider value on the basis of consumer beliefs prior to information being obtained.

The Value of Negative Information

Equation 3 makes sense when information is positive, that is, when the utilities after source s is searched exceed those before source s is searched. But a source might have positive value even if it causes Monika to lower her beliefs about the utility of a Miata. For example, she might value a colleague's candid opinion that the Miata does not meet her needs or she might value a crash-test report even if the report indicates that the car is unsafe. Thus, we need to formulate an equation, analogous to equation 3, for negative information.

Let $p_s(b)$ be Monika's subjective probability that she will ultimately purchase brand b. The subscript s indicates that this subjective probability represents her beliefs after obtaining information from source s. Define $p.(b)$ as her subjective probability before visiting source s. Without loss of generality, let $b = 1$ for the brand she is now considering.

For negative information, $p_s(1)$ is less than $p.(1)$ and equation 3 gives negative value—Monika's choices are not as good as she thought they might have been. She still sees value in the information source, but this time by recognizing that she is changing probabilities to reflect the new reality. That is, before viewing the source Monika chooses according to the $p.(b)$'s. But after viewing the source she realizes that she would have gotten utilities offered by the u_{bs}'s. Thus, the value of the consideration set *before* viewing the source (as evaluated after viewing the source) is an expectation derived from the prior $p.(b)$'s and the posterior u_{bs}'s. That is,[2]

$$(4) \qquad v_s = E_s[\max(\tilde{u}_{1s}, \tilde{u}_{2s}, \ldots, \tilde{u}_{ns})] - \{p.(1)E_s[\tilde{u}_{1s}] + [1 - p.(1)]E_s[\max(\tilde{u}_{2s}, \ldots, \tilde{u}_{ns})]\}.$$

Later we prove equation 4 gives positive values for negative information when errors are Gumbel distributed (as in a logit model).

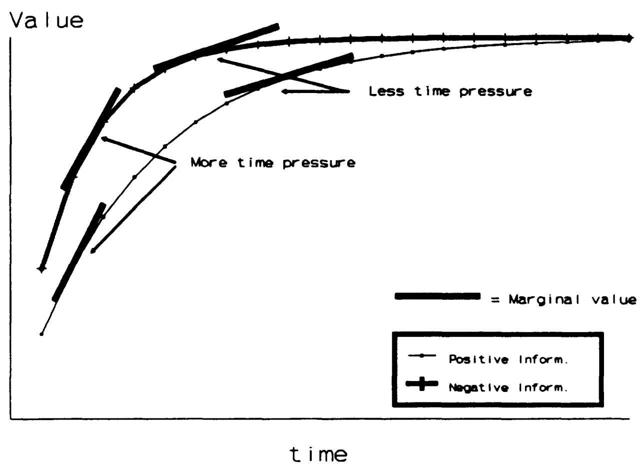
An Effect of Time Pressure

As the amount of time available, T, changes, equation 2 implies that Monika adjusts her time allocations. Without further assumptions we do not know whether the relative allocation between positive and negative sources changes. However, intuitively we expect that value functions for negative sources are steeper and level out more rapidly than value functions for positive sources. For example, a negative report that a car failed a crash test might have a more rapid impact on Monika's choice probabilities (and hence value as defined by equation 4) than would a positive report that the car passed a crash test. (With a negative crash-test report she might immediately reject the car; with a positive crash-test report she might seek more information before changing her probabilities. Recall that Monika interprets the marginal value of more time as she reads the report. She is making an exit decision.) When negative value functions are steeper initially, then level out, our model implies that Monika will spend relatively more time at negative sources under time pressure.

The intuition is illustrated in Figure 1. Here we have drawn the value function for negative information (heavy line) as steeper than that for positive information. For simplicity the maximum values are equal, but this is not necessary. Equation 2 implies that Monika allocates time to the two sources up to the point where the marginal values are equal. We indicate the marginal values by the

[2]Equation 4 assumes the consumer views the pre-information choice as that of choosing either $b = 1$ or $b \neq 1$, then choosing the maximum from the set. We might consider expanding the post-information choice the same way. Alternative models modify the conditioning of the expectations to reflect alternative assumptions. For example, we might consider a model of the form $v_s = \Sigma_b\, p_s(b)E[\tilde{u}_{bs}] - \Sigma_b\, p.(b)E[\tilde{u}_{bs}]$. For our data these alternative models imply essentially the same empirical formulation. Distinguishing among the models would require experiments formulated for that specific purpose and cannot be done with our automotive clinic data.

Figure 1
TIME PRESSURE AND NEGATIVE INFORMATION



tangents to the curves. When T is large Monika spends more time in both sources, the tangents to the right. Notice that more time is allocated to the positive source than the negative source. As T decreases the allocations to both sources decrease; the marginal values are indicated by the tangents to the left. Notice that Monika now spends more time at the negative source than the positive source. That is, the *relative* allocation of time to negative sources has increased because of the time pressure (because of a decrease in T).

To demonstrate how the intuition of Figure 1 is formalized consider the class of exponential value functions defined by $v_s(t_s) = \vartheta_s(1 - \exp[-t_s/\tau_s])$, $\vartheta_s > 0$. The time constant, τ_s, indicates how rapidly value saturates—faster saturation for negative information implies that $\tau_{negative} < \tau_{positive}$. We prove the following proposition (see appendix). The equal-asymptotes assumption is sufficient but not necessary:

> P_1 For exponential value functions with equal asymptotes consumers spend relatively more time on negative sources as time pressure increases if and only if the value function for negative information saturates more rapidly.

More general functional forms require a formal notation for the intuition of Figure 1—steeper initially with more rapid saturation. However, exponential value functions provide a flexible concave shape that illustrates the intuition.

Figure 1 and P_1 are consistent with established experimental evidence. For example, both Svenson and Edland (1987) and Wright (1974) provide evidence that consumers put more weight on negative information when placed under time pressure (see also Kanouse and Hanson 1972). In a later section we use our data to examine the impact of time pressure on the relative allocation of time to negative information.

THE ORDER IN WHICH SOURCES ARE CHOSEN

We now consider how Monika might choose the order in which to visit information sources. We continue to assume that once a source is entered, she makes the exit decision according to the time-allocation optimality conditions.

Random Order of Sources

If the value of a source does not depend on history then order does not matter (when $t_s > 0$). Monika can achieve the optimal value by visiting sources randomly as long as she leaves each source when the marginal value of time in that source falls below the cutoff value in equation 2. When the value of a source does depend on history, then search order matters. Monika may or may not do well with a random order—this is an empirical question addressed here later. At minimum, a random-order model serves as a baseline against which to compare more complicated models.

Value Priority—Myopic

Perhaps Monika would like to do better than a random order allows, but she is still myopic. She might decide to visit the source that provides the highest marginal value for her time. This can either be the marginal value when entering the source, $\partial v_{sh}(t_s = 0)/\partial t_s$, or the marginal value for some representative t_s.

Related value-priority models have been applied often. Specifically, when value is not a function of time, researchers have defined net value, n_s, as the value of an information source, v_s, minus the cost, c_s, of the information source. Cost includes time, thinking, and other costs. (See Bettman 1979; Brucks 1988; Coombs and Beardslee 1954; Hagerty and Aaker 1984; Hauser and Urban 1986; Lanzetta and Kanareff 1962; Marshak 1954; Meyer 1982; Painton and Gentry 1985; Payne 1992; Punj and Staelin 1983; Simonson, Huber, and Payne 1988; Shugan 1980; Swan 1969; and Urbany 1986.) When n_s is independent of t_s and history does not matter, the simplest and most direct solutions are the primal and dual "greedy" algorithms (Cornuejols, Fisher and Nemhauser 1977; Fisher 1980; Gass 1969). That is, the consumer chooses sources in the order of v_s/t_s or $v_s - V_o t_s$. For probabilistic models that implement these ideas, see Meyer (1982).

When value depends on time and history matters, there is no guarantee that the value-priority heuristic will lead to an optimal source order. Indeed, we demonstrate later that a value-priority heuristic can do worse than a random source-order heuristic.

Consider All Possible Source Orders

If history matters and Monika wants to make an optimal allocation, then she has to consider all possible source orders. For example, for four sources she has to consider $4 \cdot 3 \cdot 2 \cdot 1 = 24$ potential orders. (This number assumes the potential of allocating zero time to a source, otherwise there are *65* combinations of one, two, three, or four sources. More if sources can be revisited.) In addition to a large cognitive load, considering all possible source orders presents a conceptual challenge. If the value of a source can only be determined while searching it, then Monika cannot decide on the optimal source order until she searches all of them. Therefore, the choice among all possible source orders must be defined on expectations of value prior to search rather than actual value after search. (For example, Hagerty and Aaker 1984 and Simonson, Huber and Payne 1988 compute expectations of the value of information.) Of course, if the expectations are not accurate, even considering all possible source orders may not lead to an optimal search order.

For ease of exposition we refer to the process of considering all possible source orders as hyperrationality. Depending on the cognitive load that hyperrationality requires, the incremental benefits may or may not exceed the cognitive cost of using such a process.

For our data, we compute what hyperrationality would have produced had Monika known $v_{sh}(t_s)$ *a priori*, Hence providing an upper bound for alternative heuristic rules.

Look Ahead One (or More) Sources

As a compromise between a myopic and a hyperrational decision rule, Monika may decide to look ahead one source. That is, she might choose the next source to search by considering the value obtained from that source and the one that follows. In general, if history matters, such an heuristic will do better than value priority but worse than hyperrational. We define look-ahead two sources, three sources, etc. heuristics analogously. For the look-ahead heuristics (and the hyperrational algorithm) Monika needs to estimate the value function prior to search.[3] For our data we examine the performance of look-ahead heuristics based on the *a posteriori* value functions. In this way, we separate the performance of the heuristics from the quality of Monika's prescience.

DATA COLLECTION: MULTIMEDIA COMPUTER LABORATORY

There are a number of ways to examine our hypotheses. For example, we might use in-depth interviews and ask consumers to provide retrospective descriptions of how they purchased their cars, or we might follow consumers to dealers and collect verbal protocols as they go through their evaluation process. Both are viable techniques; indeed informal qualitative research forms the basis of our hypotheses. For this study we chose a multimedia computer laboratory. The laboratory is similar to the spirit of revealed preference in economics and is related to data collection using Mouselab (Johnson, Payne, and Bettman 1988; Johnson et. al. 1986; Johnson and Schkade 1989; Payne, Bettman, and Johnson 1988; Schkade and Johnson 1989), Search Monitor (Brucks 1988), Computer Laboratory (Burke et. al. 1991), and other computer simulators (Meyer and Sathi 1985; Painton and Gentry 1985; Urbany 1986) used for behavioral decision theory experiments. These are, in turn, evolutions of information display board experiments (Jacoby, Chestnut, and Fisher 1978; Painton and Gentry 1985).

The format is a multimedia personal computer.[4] Visual and verbal information is stored on a videodisc. The consumer accesses that information from the computer's keyboard, mouse, or other input device by pointing to and choosing an icon or picture that represents an information source. For example, if the consumer points to a picture of magazines, the computer displays the magazine articles and gives her a chance to peruse them. She can spend as much or little time as she wants examining the articles. The computer records all input and the time at which the consumer began and ended each activity. We had the following information available:

- Advertisements—The consumer could view actual magazine, newspaper, and/or TV advertisements on the monitor. (Driven from the videodisc the monitor becomes a television screen.)
- Interviews—The consumer could view videotapes of unrehearsed interviews of actual consumers.[5] To make the situation more realistic and to allow the consumer to choose her source, four videos were available. The consumer could choose as many or as few videos as she wanted.
- Articles—Articles designed to simulate consumer-information journals like *Consumer Reports* and other trade publications, e.g., *Road & Track*, were available. The consumer chooses one or more articles and can read them at her own pace (actual reproductions with full-color pictures appear on the screen).
- Showroom—The showroom consists of an auto walk-around, interactions with a salesperson, and a manufacturer's price sticker and brochure. In the auto walk-around the consumer sees a picture of the automobile on the screen. She chooses arrows, which scroll the image and create the impression of walking around the car. If she approaches the car door, she is given the option of opening the door

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[3]One might modify Hagerty and Aaker (1984) to formulate Bayesian or option-value heuristics in which Monika uses all available probabilistic knowledge continuously throughout the search process. We leave such heuristics for future research.

[4]We used a MacIntosh II computer, with a Mitsubishi Multisync 14" video monitor, a Truvision New Vista video card, and a Pioneer 4200 laser videodisc. The software was written in Macromind Director. A videotape illustrating the computer laboratory is available from the authors.

[5]On the basis of experimentation and experience (Urban, Hauser, and Roberts 1990) we have found that the most realistic word-of-mouth videos appear to be produced either with unrehearsed and unscripted consumers or with professional improvisational actors given general topics and information. Videotaping was done by a professional production company. The auto company is now experimenting with formats in which the consumer chooses the topics as well as the source.

and examining the interior. Similarly, she can look under the hood and inside the trunk.

At any time during the auto walk-around she can ask the salesperson questions. She does this by choosing a topic from a menu. The answer is given by a videotaped image of an actual salesperson. If she so chooses, she can view the manufacturer's sticker and/or brochure.

The advertisement, interview, article, and showroom information were chosen, on the basis of qualitative consumer interviews, manufacturer and dealer experience, and prior research (Furse, Punj and Stewart 1984; Kiel and Layton 1981; Newman and Staelin 1972; Punj and Staelin 1983; Westbrook and Fornell 1979), as representative of the types of information that consumers access in their search for information about automobiles.

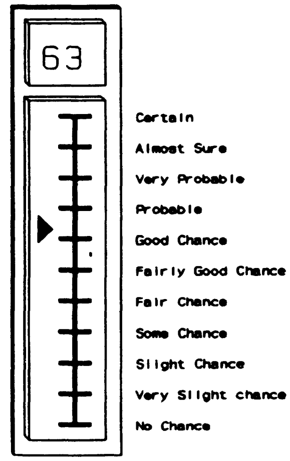
From a data collection viewpoint the important characteristics of the multimedia laboratory are that the consumer chooses freely which sources to search, the order in which to search the sources, and the amount of time to spend in each source. She can exit a source at any time and return to that source as often as she chooses. To make the decision process real, the consumer is given a fixed budget of time in which to search. On the screen from which the consumer selects a source (or an option within a source), she sees realistic cues that tell her how long respondents typically spend in a source.

Context and Sample

We examine data from a prelaunch forecasting project conducted to test consumer reaction to a new two-seated sporty car, the Buick Reatta convertible. The advertisements were made available by the agency, and the interviews and showroom visits were produced by a professional studio. The salesperson was a Boston-area Buick salesman. Because the data were collected, in part, to forecast sales of the Reatta, the project used a test-car/control-car design. Two-thirds of the sample searched for information on the Reatta; one-third for the Mazda RX-7 convertible. Though we expected consumer preferences for the Reatta and the RX-7 to differ, we hoped the process by which consumers search for information does not. To the extent that sample sizes allowed comparisons, we found no significant differences between the Reatta and the RX-7 samples in the subsequent analyses reported here.

In addition to forecasting sales of the Reatta, General Motors wanted to test the ability of the computer laboratory to reproduce a showroom with a real car present. Hence, for one-third of our sample, chosen randomly, when consumers selected the showroom visit they received a message to call for an attendant. Instead of seeing the showroom on the computer they were taken to view the actual automobile in a simulated showroom. The same salesman who had been videotaped was there to answer questions (from the same script). When consumers completed the showroom visit, they returned to the computer to search other sources. If they so chose, they were allowed to revisit the showroom. Each visit was timed.

Figure 2
MEASURE OF PURCHASE INTENT



To ensure external forecast validity and that consumers would have an interest in information on the Reatta and the RX-7, consumers were prescreened by telephone on whether they would consider purchasing a two-seated sports car as their next car and whether they planned to spend at least $20,000 on the purchase. The initial sample was chosen from the registration records of consumers who had purchased a sports car in the last two years. Those consumers who qualified were invited to participate in our study. They were promised a $25 incentive and given a time and location at which to appear. In total, 956 calls were made, 561 consumers were contacted, 280 qualified, and 204 agreed to participate. The final sample of 177 were assigned randomly to treatments according to these proportions.

Before and after gathering information consumers were asked to indicate the probability that they would purchase the target car (Reatta or RX-7, whichever the consumer saw).

Purchase Intent

Consumers indicated the probability that they would purchase a car using a thermometer scale with the eleven verbal anchors which are commonly used in purchase intent scales (Juster 1966) (see Figure 2). The consumer provides a subjective probability after visiting an information source by using the mouse to drag a pointer from the prior value (obtained by an earlier question). As the arrow moves, the intent value, e.g., 63 (chances in 100), changes automatically. When the arrow passes the verbal anchors they are highlighted. If no action is taken, the prior answer is not changed; it becomes the answer to the current question, implying that the information source did not change the consumer's purchase intent.

The consumer is given the opportunity to change her purchase intent after exiting any information source. The first measure of purchase intent is on the basis of a picture of the target car. The final measure is taken after the consumer indicates she is done searching for information.

Purchase intent is a laboratory measure by which a consumer estimates the probability of purchasing the target car at a later date. By stating some number other than 0.0 or 1.0, the consumer acknowledges that she is likely to get more information before making a final decision. For example, she might talk to a spouse, assess her tastes, examine her bank account, or even try to get a firm price from a salesperson. We recognize that a purchase intent measure is a noisy estimate of purchase probabilities, but there is evidence that the larger the purchase intent measure, the larger the purchase probability (see Jamieson and Bass 1989; Juster 1966; Kalwani and Silk 1983; McNeil 1974; Morrison 1979). In our theoretical development we refer to purchase probabilities; in our empirical work we use purchase intent measures under the assumption that they are monotonically increasing in purchase probabilities.

Information about a brand can change that brand's purchase probability in many ways. If the information is positive it may increase the consumer's perception of the mean utility, hence increasing the purchase probability. Similarly, negative information may decrease the purchase probability. But information can also reduce risk by decreasing the consumer's uncertainty. Decreased risk means an increased certainty equivalent and thus an increased purchase probability (e.g., see Meyer 1982; Meyer and Sathi 1985; Roberts and Urban 1988).

To specify how purchase probabilities relate to the value of an information source we need to elaborate equations 3 and 4. We address this modeling in a later section.

Budget Constraint on Time

It is less costly to search for information within the laboratory than would be the case if the consumer had to visit a real showroom, talk to colleagues, etc. With no time limit the consumer might want to visit all sources to see how they are simulated on the computer. We attempted to minimize these threats to the measurement in two ways. First, by selecting consumers who were in the market for a sporty car and potentially interested in the Reatta or RX-7, we hoped that they would want to gain realistic information on the car rather than "play" with the computer or "tinker" with simulated sources. Second, we limited the time they could spend searching for information. After a number of pretests we selected times that gave the consumers enough time to search but were perceived as a real time constraints.

In initial questions consumers indicated the sources they normally use to gather information on cars and how often they use these sources, for example, how many dealers they visit. On the basis of these answers most consumers were designated low, medium, and high searchers with allocations of 7, 10, and 13 minutes in the laboratory.[6] (See related taxonomies in Claxton, Fry, and Portis 1974; Furse, Punj and Stewart 1984; and Kiel and Layton 1981.) We chose these times in an attempt to set the time constraint in the laboratory so that consumers searched the same number of sources in the laboratory that they would when normally searching for a car. The manipulation of the budget constraint was reasonable in the sense that for each group the number of sources searched in the laboratory was within a standard deviation of the number of sources that consumers reported. For example, on average consumers searched 2.41 sources in the laboratory and indicated (prior to the laboratory) that they searched 2.46 sources when gathering information for an automobile purchase.

The Laboratory as a Representation of Information-Search Behavior

By design consumers can search for information faster in the laboratory than they would otherwise. Furthermore, this acceleration varies by source. For example, a showroom visit might take a few hours for Monika, but only a few minutes in the laboratory. In contrast, the acceleration of the time it takes her to read *Consumer Reports* might be less dramatic. The laboratory also does not simulate fixed costs such as driving to visit a dealer before information can be obtained. Therefore, it would be dangerous to project from the laboratory the relative amount of time consumers spend in each source.

However, the various information sources made available in the laboratory are still information sources. The consumer faces a binding budget constraint on her time and thus faces both a time-allocation and source-order problem. If the consumers in the sample are interested in the target car and desire real information, then it is likely that they will react to the laboratory with the same allocation process they use when searching for information on automobiles. Furthermore, this process should be the same whether they are searching for information on the Reatta or the RX-7 and whether the showroom is represented on the computer or by a real-car showroom mock-up. Therefore, as long as we limit our analyses to the allocation of time *within* the laboratory and make no attempt to compare accelerated to actual time, we should be able to examine the theory developed in this study. On the plus side, the laboratory allows unobtrusive observation with free choice of source and time as an endogenous variable.

[6]In the field a few consumers were given constraints that were a little more or a little less than these numbers. This variation actually proved useful in examining the impact of positive vs. negative information. Naturally, these consumers where excluded from any analysis segmented by time constraint.

DATA CHARACTERISTICS

Search Behavior

Table 1 summarizes the selections consumers made with respect to which sources to search. Recall that they were free to select which sources to search, the order in which to search them, and the time spent in each. Table 1 also summarizes the average amount by which consumers changed their purchase probabilities on the basis of the source. Because some consumers increased their probabilities and some decreased their probabilities, we also report the average absolute change.

It is interesting that the percentage of time a source is selected first, the percentage of consumers selecting a source, the time spent in a source, and the average change in purchase probabilities are clearly related. We hope the models developed are consistent with this simple look at the data. It is also gratifying that the percentage of times consumers use a source in the laboratory is related to the percentage of times they report using that source when they are searching for information on new cars. However, because the actual cost of a source may vary from our study, these results must be interpreted with caution.

Table 1 suggests the showroom is the most valuable source in the laboratory. When we estimate more complex models we compare the parameter estimates to this observation on the unadjusted averages.

Purchase Intent Measures

Our sample contains data from consumers who used a video showroom and consumers who used a single-car showroom mock-up with a real salesperson. Fortunately, for our sample there was no significant difference in the purchase intent measures between the video showroom and the showroom mock-up (see Weinberg 1992). The difference was not significant for either final intent ($F = .22$) or the change in intent before and after the showroom ($F = .05$). However, the laboratory did distinguish between the Reatta and the RX-7 ($F = 4.33$ for final purchase intent and $F = 2.96$ for the change in intent).

Our hypotheses make no predictions about whether intent should increase or decrease because of information. However, for the record, in our laboratory, among consumers who changed their intent because of information, 60% increased purchase intent and 84% of the patterns are monotonic, either all up or all down. The variance in purchase intent decreased as more sources were searched.

MODELS VERSUS DATA

We now choose a specific functional form for the value function, estimate the resulting model with data collected in the multimedia laboratory, and compare predictions on the basis of the model to observed consumer time allocations and source order.

The Allocation of Time

Value of information as a function of time. We expect the value function to have two properties: First, once a consumer is in a source she experiences decreasing marginal returns, that is, she gets more information at the beginning of her stay than at the end; second, there will be some threshold effect, some time cost of entering a source. For example, if Monika seeks information from a Mazda showroom she needs to drive to that showroom. For her, value begins only after she has reached the showroom. For the laboratory, we acknowledge that this threshold might be zero.

Analytically, this means there is some threshold time, θ_s, such that the value of a source is zero for time less than the threshold and becomes positive only after she has invested at least θ_s seconds in the source.[7] These properties are illustrated in Figure 3.

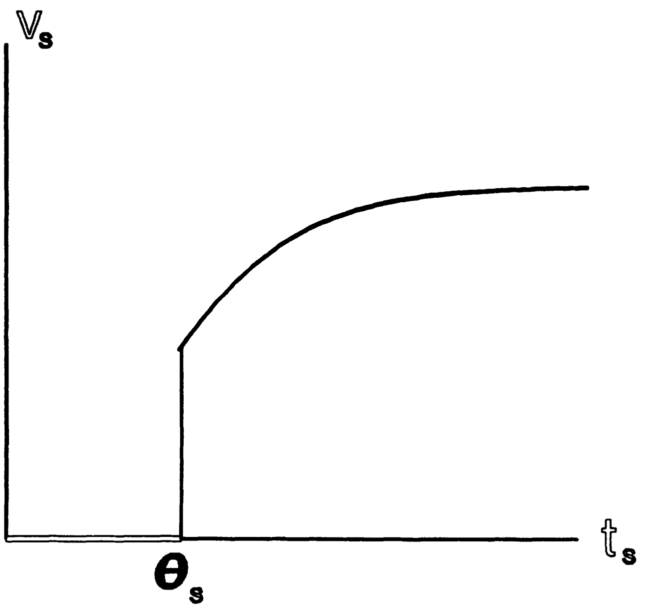
Ideally we would like the parameters to vary for positive and negative sources. However, because (1) we have relatively few (69) observations of sources providing negative information, (2) history-dependence implies many parameters need to be estimated, and (3) the exponential function in P_1 is difficult to linearize, we need to make practical simplifications in our data analysis. We chose the *log(·)* function and did not estimate sep-

[7]Because the consumer can always choose to ignore information, the value she obtains from an accurate source is never a negative number. (Recall that the value of negative information is a positive number.) Note that this does not address the issue that a salesperson can give information that is misleading and therefore of negative value. Such information is not given in the laboratory, hence the assumption of non-negative value clearly applies to our data. But applications beyond the laboratory may need to address this point. Finally, note that though the value of the source is assumed positive, the net value can be negative if the cost exceeds value.

Table 1
SEARCH BEHAVIOR—AVERAGE RESULTS

SOURCE	*FIRST SOURCE*	*PERCENT USING*	*PRIOR USE*	*TIME IN SOURCE*	*CHANGE IN PROB.*	*ABSOLUTE CHANGE*
Showroom	48%	81%	77%	174″	.036	.084
Interview	19%	61%	53%	157″	.028	.040
Articles	24%	65%	69%	107″	.013	.050
Advertisements	9%	38%	42%	51%	.016	.016

Figure 3
VALUE OF INFORMATION AS A FUNCTION OF TIME



arate parameters for negative information. The $log(\cdot)$ function exhibits decreasing marginal returns and is used often to measure perceptual value (e.g., decibels is a $log(\cdot)$ function of sound amplitude). Empirically, it is difficult to separate a $log(\cdot)$ function from an exponential function.

When we added a threshold, the chosen function was given by equation 5, where a_{sh} and b_{sh} are parameters to be estimated. Note that we have made the dependence on the history of past information source exposure explicit by allowing the parameters of the value function to vary on the basis of history, h. This allows the value of one source, say the showroom, to depend on whether another source, for example, articles, has been searched.

$$v_s(t_s) = \begin{cases} a_{sh} + b_{sh} \log t_s & \text{if } t_s \geq \theta_s \\ 0 & \text{if } t_s < \theta_s \end{cases} \tag{5}$$

The value of an information source. Purchase intent probabilities are the only surrogates for value available in the automotive-clinic data. We formalize the relationship between consumer utility and probability with logit-like models. (Recall that we assume purchase probability is monotonic in purchase intent.) Specifically, we assume the consumer utilities, $\tilde{u}_{bs}$'s, are independently Gumbel distributed random variables where u_{bs} is the observable component, the mode of the distribution. Then, by the properties of the Gumbel distribution (Ben-Akiva and Lerman 1985, p. 105), the purchase probabilities, $p_s(b)$, are given by the logit model in equation 6 where we have subsumed the scaling parameters into the scaling of the utilities:

$$p_s(b) = \frac{e^{u_{bs}}}{\sum_{b=1}^{B} e^{u_{bs}}}. \tag{6}$$

An analogous equation applies to $p_{\cdot}(b)$.

Positive information. After gathering information from source s, the value of the consideration set is $E_s[max(\tilde{u}_{1s}, \tilde{u}_{2s}, \ldots, \tilde{u}_{ns})]$. According to properties 2 and 7 of the Gumbel distribution (Ben-Akiva and Lerman 1988, p. 105), this value is given by $log\ \Sigma_b\ exp(u_{bs})$. Similarly, prior to gathering information from a source, the value of the consideration set is given by $log\ \Sigma_b\ exp(u_{b\cdot})$. When Monika realizes that u_{1s} increases she considers the value of the information to be the increase in the expected value of choosing from the choice set as given by equation 3.

Because the laboratory only provides information on brand *1*, utilities do not change for $b \neq 1$, thus we define $\alpha \equiv \Sigma_{b \neq 1}\ exp(u_{bs}) = \Sigma_{b \neq 1}\ exp(u_{b\cdot})$. Then we solve equation 6 to obtain $u_{1s} = log\{p_s(1)/[1 - p_s(1)]\} + log\ \alpha$. An analogous equation gives $u_{1\cdot}$. We now substitute back into equation 3 and obtain

$$v_s(positive) = \log[1 - p_{\cdot}(1)] - \log[1 - p_s(1)]. \tag{7}$$

Negative information. For negative information we use equation 4. Recognizing that $E_s[max(\tilde{u}_{2s}, \ldots, \tilde{u}_{ns})] = log[\alpha]$ and using the preceding equations for utilities we substitute into equation 4 to obtain the value of negative information as

$$v_s(negative) = p_{\cdot}(1)\{\log[1 - p_s(1)] - \log p_s(1)\} - \log[1 - p_s(1)]. \tag{8}$$

A common representation. Equations 7 and 8 are derived for purchase probabilities, but the data are on the basis of purchase intent probabilities. We want a measure of value that is robust with respect to assumptions about the translation of purchase intent to purchase probabilities (see appendix for proof).

> P_2 The value of positive information and the value of negative information are each monotonically increasing in the absolute change in purchase intent.

A formulation based on P_2 has the advantage that we can use the same equation for positive and negative information. This is important when examining history dependence with our sample sizes.

In summary, we use the absolute change in purchase intent as a reasonable measure of the value of an information source.[8]

[8]Lanzetta and Kanareff (1962) also propose Δp for positive information on the basis of utility maximization arguments of Marshak (1954) and Coombs and Beardslee (1954). Other models might also yield $|\Delta p|$ as a proxy for value. Our data analysis uses the property that $|\Delta p|$ is a proxy for v_s.

Table 2
REGRESSION OF VALUE ON LOG TIME

VARIABLE	ESTIMATE	t-VALUE
Showroom as a first source	3.3[1]	5.8
Showroom as a subsequent source	1.8[1]	3.1
Interviews as a first source	1.9[1]	2.8
Interviews as a subsequent source	.8[2]	1.4
Articles as a first source	1.9[1]	2.8
Articles a subsequent source	1.4[1]	2.1
Advertisements as a first source	1.3[3]	1.3
Advertisements as a subsequent source	.5	.6
STATISTICS		
F-statistic	10.8	
Multiple R	.45	
Adjusted R^2	.18	
Significance: 1 = .05, 2 = .10, 3 = .15		

Estimation

We estimate the parameters of equation 5 by regressing the absolute change in intent measures on a dummy variable indicating which source was chosen (this gives us a_{sh}'s) and the dummy multiplied by the logarithm of the time in the source (this gives us the b_{sh}'s). The data is on the basis of 351 total sources that the consumers searched with the information laboratory.[9]

In none of the regressions were the a_{sh}'s significant. For example, for the second set of regressions (described following) the comparison between a regression with the a_{sh}'s and without the a_{sh}'s resulted in no significant improvement (F(7,336) = .453). We suspect this non-significance is a laboratory effect; sources outside the laboratory may have non-zero fixed costs.

We specify the dependence of value on previously visited sources in three ways: In the first set of regressions (null model) we estimate the parameters independently of history; In the second, we estimate one set of parameters if the source is entered first and a second set of parameters if the source is not entered first (this regression is significantly better than the null model (F(4,343) = 6.34)); and in the third set of regressions, we estimate a different set of parameters depending upon whether a source was chosen first, second, third, or fourth and later. This regression does not result in a significant improvement relative to the second regression (F(8,335) = 0.853). Therefore, the best regression (of the regressions that we ran) models history by first source versus subsequent ones. It includes the b_{sh}'s and an overall constant, but not the a_{sh}'s (see table 2).

The regression in Table 2 is encouraging—the results have *post facto* face validity. It is reasonable, on the basis of our prior experience in the automobile industry, that the showroom provides the highest marginal value and advertising the least. As expected, every source provides less marginal value if it is a subsequent source rather than the first. The regression is significant as are most of the coefficients. All the coefficients have the proper sign. If we compare Table 2 with the average results in Table 1, we see that the information source with the largest coefficient is the one chosen most often and chosen first most often. It is also the source at which consumers spend the most time. However, the ability to fit a model does not guarantee that the optimality conditions hold.

Do the Optimality Conditions Hold?

A stronger test of the theory is whether the optimality conditions in equation 1 hold for observed time allocations. The optimality conditions state that the consumer will continue collecting information from a source as long as the marginal benefit of that information exceeds the marginal value of free time. At optimality, the marginal values of information, $\partial v_{sh}/\partial t_s$, are equal across sources. For the logarithmic function in equation 5 this implies that $t_s = b_{sh}/constant$ for all sources. We eliminate the unknown constant to derive equation 9:

$$(9) \qquad \frac{t_s}{\sum_{s=1}^{s} t_s} = \frac{b_{sh}}{\sum_{s=1}^{s} b_{sh}}.$$

There is no guarantee that the regression will select coefficients such that equation 9 is satisfied. The regression relates value (the absolute change in intent measures) to time at a source, whereas equation 9 relates the ratio of the estimates to the ratio of time. Indeed we have constructed an example in which the regression for value (equation 5) has an excellent fit (R^2 = .88), but the parameter ratio has a .00 correlation with the time-allocation ratio (equation 9).[10]

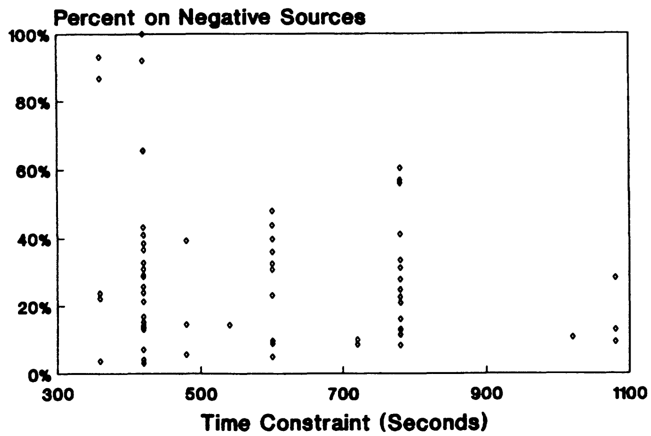
Define R_t as the time ratio on the left side of equation 9 and define R_b as the ratio of the parameter estimates on the right.

Though there is one set of b_{sh}'s, R_b can vary by consumer. For example, Monika might visit the showroom first; her R_b ratio would use the b_{sh} from showroom as a first source and the b_{sh}'s from interviews, advertisements, and articles as subsequent sources. If another consumer, whom we will call Rowland, used only interviews and articles, his R_b ratio would be on the basis of only those sources. For each consumer we create a vector of R_b ratios and compare them to that consumer's vector of R_t ratios. The average values of these ratios are

[9]Our analysis is on the basis of those consumers who made at least one change in probabilities as a result of information. Consumers who made no change, "flat-liners," presumably had sufficient information prior to coming to the laboratory. Value cannot be measured for the flat-liners. When flat-liners are included in the regression we get the same relative results with smaller coefficients.

[10]Example available from the authors.

Figure 4
THE EFFECT OF TIME CONSTRAINTS



SOURCE	R_b-RATIO	R_t-RATIO
Showroom	.53	.51
Interviews	.22	.32
Articles	.31	.25
Advertisements	.14	.12

The correlation of the four averages is very high at .94 as is the correlation across consumers which is .70. A more conservative test eliminates consumers who search only one source and eliminates one source per person.[11] That correlation is a respectable .52. These correlations are conservative because all approximations made in the estimation work against a good match between the parameter ratios and the time-allocation ratios. On the basis of these correlations we postulate that the optimality conditions are not a bad approximation to consumer time allocations. If these results survive future tests, then it may be possible to use time allocations to infer the relative value of a source.

Relative Allocations to Negative-Information Sources

Though sample sizes limit us to estimating a model in which a_{sh} and b_{sh} were the same for both positive and negative information, we can examine the aggregate implications of P_1. (Variation in the parameters by positive versus negative sources work against fitting equation 5 suggesting that both the estimation and ratio comparison are conservative tests.)

Figure 4 plots the percentage of time spent on negative sources versus the time constraints for the 69 instances in which consumers found negative value in some source. The correlation is small (*.21*), but significant (*.05 level*). Given the aggregate nature of the analysis, the correlation in Figure 4 is promising. (In our laboratory a form of self-selection makes the correlation conservative. Because consumers were assigned to constraints on the basis of previous search behavior, those with tighter constraints may have felt less time pressure than a random assignment would imply.) Perhaps future experiments will analyze the implications of P_1 more completely.

[11]If we know a consumer chooses S sources, we can predict the S^{th} source chosen from knowledge of the identities of the first $S - 1$ sources. $S = 1$ eliminates a consumer from the correlation.

Table 3
OPTIMAL VALUES (PERCENT CHANGE IN INTENT)

ALLOCATION (seconds)	*420*	*600*	*780*
Showroom 1st	29.4	31.5	33.1
Interviews 1st	26.6	28.6	30.0
Articles 1st	23.9	25.7	27.0
Advertisements 1st	24.9	26.8	28.1
Random	26.2	28.1	29.6

Does Source Order Have a Large Impact on the Optimal Value of Information?

For the value functions estimated in Table 2 the history dependence is first versus subsequent source. Therefore, a hyperrational model is equivalent to a look-ahead-one-source model. If the consumer is prescient about the value she will obtain from a source, then a look-ahead-one-source model gives her optimal value. Once the first choice is made the order in which she visits subsequent sources does not matter because the marginal values do not change.

To determine how close each heuristic comes to optimality we use the parameters in Table 2. (These parameters apply to all consumers in the sample; for any given consumer they are approximate.) Table 3 uses equation 9 to compute the optimal allocations and equation 5 to compute the optimal value. These allocations and values vary on the basis of which source is visited first. Because the dependent variable in the estimation (Table 2) is purchase intent, the units in Table 3 are the percentage by which purchase intent changes. For the hyperrational and look-ahead-one-source heuristics table 3 suggests that it is best to visit the showroom first. In our data showroom also has the highest marginal value and, hence, would be visited first according to the value-priority heuristic. In contrast, a random heuristic would provide a value less than optimal as computed from Table 3. (These numbers apply to percentage changes in purchase intent. Because P_2 establishes only monotonicity, percentage changes in value are interpreted with caution.)

Though for our data both the value priority and look-ahead-one-source heuristics predict the same first source, this is not always the case. For example, if articles and advertising were the only sources then value-priority would predict articles first because articles provide a higher marginal value (b_{s1} of 1.9 versus 1.3). Look-ahead-one-source and hyperrational would predict advertising first because advertising provides the higher value (23.9 versus 24.9 for T = 420 in Table 3). This reversal occurs because articles are much better than advertising as a second source (b_{s2} of 1.4 versus .5).

Using this concept and keeping the first-source b_{s1}'s constant, it is easy to create an example with all four sources in which advertising is the best first choice. With b_{s2}'s of 3.2, 1.8, 1.8, and .01 for showroom, interviews, articles, and advertising, respectively, the optimal value (T = 420) with the look-ahead algorithm (advertising first) is 38.2 which is higher than the optimal value with the value-priority algorithm (showroom first) that gives 34.4. (With these parameters a random heuristic provides a total information value of 35.2, larger than that provided by a value-priority heuristic but less than that provided by a look-ahead heuristic.) Therefore, in principle, alternative source-order heuristics provide distinguishable predictions.

In summary, the hyperrational, look-ahead-one-source, and value-priority heuristics all suggest that the consumer visit the showroom first—48% of the consumers visited the showroom first. However, for slight perturbations in the data we can create examples in which a look-ahead heuristic gives an 11% improvement over a value-priority heuristic and a 7% improvement over a random heuristic.

DISCUSSION

Summary

We explore a cost/benefit model of how consumers allocate time when searching for information. Specifically, we focus on the use of information to evaluate an automobile for inclusion in a consideration set. We assume that (given a source order) consumers allocate time by maximizing value subject to a time-budget constraint. This assumption establishes optimality conditions. For positive information, value is the increase in the expected utility of the consideration set. For negative information, value is the utility the consumer now expects to get minus the utility she would have gotten had she chosen (perhaps erroneously) without the information. We demonstrate for Gumbel-distributed errors that value is monotonically increasing in the absolute change in purchase intent for both positive and negative information. We also argue that if negative value functions reach their asymptotes faster, consumers should spend proportionally more time on negative information when faced with time pressure. For the source order we explore random, hyperrational, value-priority, and look-ahead (heuristic) rules.

We examine our hypotheses with data collected for the prelaunch forecast of the Buick Reatta. The data are interesting because consumers are allowed, subject to time constraints, free choice of source order and free choice of time within source. We use the data to estimate the parameters of a simple value function and to examine some implications of the cost/benefit models.

Consumer time allocations appear to be correlated with those predicted by the optimality conditions and there is a small but significant relationship between time constraints and the percentage of time in negative sources. On the basis of estimated parameters, a hyperrational choice of source order does better than a random choice of source order, but only slightly. Value-priority and look-ahead do well in the data, but, in principle, are distinguishable.

Future Directions

The real contribution of a "rational" model of consumer time allocation is that it frames many issues. It explains some of the aggregate patterns in our data even though the estimation of value required a number of approximations. Perhaps most provocative is the fact that simple source-order heuristics (look-ahead or random) are not all that bad. Our evidence on negative sources is interesting, but constrained by the low sample sizes resulting from natural selection.

We see many potential experiments. One might create sources with more negative information and randomly assign consumers to situations with negative and with positive sources. If time constraints are also varied, proposition 1 can be explored. With sufficient sample, separate value functions can be estimated for positive and for negative information. In an experiment one might create some sources that have high first-choice values but low second-choice values. For such sources the value-priority and look-ahead heuristics give different predictions. The experiments of Brucks (1988), Burnkrant (1976), and Urbany (1986) each can be modified to consider time as an endogenous choice. Unless the researcher fixes the time in a source, value can not be manipulated independently; only the value function can be manipulated.

Simonson, Huber, and Payne (1988) explore the relationship between prior brand knowledge and source order. In their experiments they use a random stopping rule in which the consumer believes that the next information source may be the last. Even though random stopping rules favor the value-priority heuristic over look-ahead heuristics, they find evidence consistent with dynamic look-ahead processing. (They find the "same brand" and "same attribute" decision variables to be significant.) It would be interesting to extend their experiments with time constraints rather than a random stopping rule. Theoretically, one might use their model, based on Hagerty and Aaker (1984), to compute the option value of an information source (the entry decision) and compare the value derived from the time allocation model (the exit decision). Empirically, such a comparison could quantify consumer prescience which is likely to vary on the basis of expertise and prior brand knowledge.

In our data the source with the highest initial value is also the source for which the optimality conditions imply the highest time allocation. But this need not be true. One value function may increase rapidly to an asymptote whereas another may increase more slowly but maintain higher marginal values for larger time allocations. Experiments with such sources would distinguish time allocations on the basis of the optimality conditions from alternative hypotheses, such as the consumer spending more time in the higher value source.

Finally, though the theoretical result that purchase intent can be used as a surrogate for value is interesting, the allocation theory might be improved if value is on the basis of more-detailed measures. Improved data collection that measures changes in consumer perceptions of product/service attributes and consumer uncertainty might provide better dependent measures. Long-term tracking could explore the link from purchase intent to purchase probability.

APPENDIX
PROOFS OF THE PROPOSITIONS

Proposition 1

Exponential value functions are defined by $v(t) = \vartheta(1 - e^{-t/\tau})$ where we have dropped the subscript on information source, s, without loss of generality. The condition of the proposition is that $\tau_n < \tau_p$ where the subscripts n and p indicate negative and positive information respectively. Because all value functions are concave at optimality, when T increases so does the total allocated to $T - t_o$; hence we define $T \equiv t_p + t_n$ for purposes of this proof. We need to prove that $df/dT < 0$ where $f \equiv t/T$. *indicates optimality.

Optimality implies that $\partial v_n(t_n^*)/\partial t_n = \partial v_p(t_p^*)/\partial t_p$. Setting $t_n^* = T - t_p^*$ and differentiating we get:

$$\frac{v_n}{\tau_n} e^{-t^*_n/\tau_n} = \frac{v_p}{\tau_p} e^{-(T-t^*_n)/\tau_p}.$$

Solving for t_n^* yields

$$t_n^* = \left(\frac{\tau_n \tau_p}{\tau_n + \tau_p}\right) \log \frac{v_n \tau_p}{v_p \tau_n} + \frac{T\,\tau_n}{\tau_n + \tau_p}.$$

By direct calculation, $df/dT = (Tdt_n^*/dT - t_n^*)/T^2$. Substituting we obtain

$$\frac{df}{dT} = -\frac{1}{T^2}\left(\frac{\tau_n \tau_p}{\tau_n + \tau_p}\right) \log \frac{v_n \tau_p}{v_p \tau_n},$$

which is negative whenever $\vartheta_n = \vartheta_p$ and $\tau_n < \tau_p$. Note that equality of the scaling constants is sufficient, but not necessary. ■

Proposition 2

Positive information. Holding $p_*(1)$ constant, we differentiate equation 7 with respect to $p_s(1)$.

$$\frac{\partial v_s}{\partial p_s(1)} = \frac{1}{1 - p_s(1)} > 0$$

Thus, v_s increases whenever Δp increases.

Negative information. Holding $p_*(1)$ constant we differentiate equation 8 with respect to $p_s(1)$:

$$\frac{\partial v_s}{\partial p_s(1)} = \frac{\Delta p}{p_s(1)[(1 - p_s(1)]}.$$

When information is negative, $\Delta p < 0$. Therefore, $\partial v_s/\partial \Delta p < 0$. Finally, with $p_*(1)$ constant, initial purchase intent is constant, thus Δp is monotonic in post-source purchase intent, and we have the result. ■

REFERENCES

Ben-Akiva, Moshe and Steven R. Lerman (1985), *Discrete Choice Analysis: Theory and Application to Travel Demand.* Cambridge, MA: MIT Press.

Bettman, James R. (1979), *An Information Processing Theory of Consumer Choice.* Reading, MA: Addison-Wesley.

Brucks, Merrie (1988), "Search Monitor: An Approach for Computer-Controlled Experiments Involving Consumer Information Search," *Journal of Consumer Research*, 15 (June), 117–21.

Burke, Raymond R., Barbara E. Kahn, Leonard M. Lodish, and Bari Harlam (1991), "Comparing Dynamic Consumer Decision Processes in Real and Computer-Simulated Environments," working paper, Marketing Science Institute, Cambridge, MA.

Burnkrant, Robert (1976), "A Motivational Model of Information Processing Intensity," *Journal of Consumer Research*, 3 (June), 21–30.

Claxton, John D., Joseph N. Fry, and Bernard Portis (1974), "A Taxonomy of Prepurchase Information Gathering Patterns," *Journal of Consumer Research*, 1 (December), 35–43.

Coombs, C. H. and David Beardslee (1954), "On Decision Making Under Uncertainty," in *Decision Processes*, R. M. Thrall, C. H. Coombs, and R. L. Davis, eds. New York: Wiley, 255–86.

Copeland, Melvin T. (1923), "Relation of Consumer's Buying Habits to Marketing Methods," *Harvard Business Review*, 1 (April), 282–89.

Cornuejols, Gerald, Marshall L. Fisher, and George L. Nemhauser (1977), "Location of Bank Accounts to Optimize Float: An Analytic Study of Exact and Approximate Algorithms," *Management Science*, 23 (April), 789–810.

Fisher, Marshall (1980), "Worst Case Analysis of Heuristic Algorithms," *Management Science*, 26 (January), 1–17.

Furse, David H., Girish N. Punj, and David W. Stewart (1984), "A Typology of Individual Search Strategies Among Purchasers of New Automobiles," *Journal of Consumer Research*, 10 (March), 417–31.

Gass, Saul I. (1969), *Linear Programming: Methods and Applications*, 3rd ed., New York: McGraw-Hill.

Hagerty, Michael R. and David A. Aaker (1984), "A Normative Model of Consumer Information Process," *Marketing Science*, 3 (Summer), 227–46.

Hauser, John R. and Glen L. Urban (1986), "The Value Priority Hypotheses for Consumer Budget Plans," *Journal of Consumer Research*, 12 (March), 446–62.

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

Irwin, Francis R. and W. A. Smith (1957), "Value, Cost, and Information as Determiners of Decision," *Journal of Experimental Psychology*, 54 (September), 229–32.

Jacoby, Jacob, Robert W. Chestnut, and William A. Fisher (1978), "A Behavioral Process Approach to Information Acquisition in Nondurable Purchasing," *Journal of Marketing Research*, 15 (November), 532–44.

Jamieson, Linda F. and Frank M. Bass (1989), "Adjusting

Stated Intention Measures to Predict Trial Purchase of New Products: A Comparison of Models and Methods," *Journal of Marketing Research*, 26 (August), 336–45.

Johnson, Eric J., John W. Payne, and James R. Bettman (1988), "Information Displays and Preference Reversals," *Organizational Behavior and Human Decision Processes*, 42, 1–21.

———, ———, David A. Schkade, and James R. Bettman (1986), "Monitoring Information Processing and Decisions: The Mouselab System," working paper, Center for Decision Science, Fuqua School of Business, Duke University.

——— and David A. Schkade (1989), "Heuristics and Bias in Utility Assessment: Further Evidence and Explanations," *Management Science*, 35 (April), 406–24.

Juster, Frank T. (1966), "Consumer Buying Intentions and Purchase Probability: An Experiment in Survey Design," *Journal of the American Statistical Association*, 61, 658–96.

Juster, F. Thomas and Frank P. Stafford (1991), "The Allocation of Time: Empirical Findings, Behavioral Models, and Problems of Measurement," *Journal of Economic Literature*, 29 (June), 471–522.

Kalwani, Manohar U. and Alvin J. Silk (1983), "On the Reliability and Predictive Validity of Purchase Intention Measures," *Marketing Science*, 61 (September), 243–86.

Kanouse, David E. and L. Reid Hanson, Jr. (1972), "Negativity in Evaluations," in *Attribution: Perceiving the Causes of Behavior*, E.E. Jones, et. al, eds. New York: General Learning Press, 27–46.

Kiel, Geoffrey C. and Roger A. Layton (1981), "Dimensions of Consumer Information Seeking Behavior," *Journal of Marketing Research*, 18 (May), 233–39.

Lanzetta, John T. and Vera T. Kanareff (1962), "Information Cost, Amount of Payoff, and Level of Aspiration as Determinants of Information Seeking in Decision Making," *Behavioral Science*, 7 (October), 459–73.

Marshak, Jacob (1954), "Towards an Economic Theory of Organization and Information," in *Decision Processes*, R. M. Thrall, C. H. Coombs, and R. L. Davis, eds. New York: Wiley, 187–220.

McNeil, J. (1974), "Federal Programs to Measure Consumer Purchase Expectations, 1946–73: A Post-Mortem," *Journal of Consumer Research*, 1 (December), 1–10.

Meyer, Robert J. (1982), "A Descriptive Model of Consumer Information Search Behavior," *Marketing Science*, 1, (Winter), 93–121.

——— and Arvind Sathi (1985), "A Multiattribute Model of Consumer Choice During Product Learning," *Marketing Science*, 4, (Winter), 41–61.

Morrison, Donald G. (1979), "Purchase Intentions and Purchase Behavior, *Journal of Marketing*, 43 (Spring), 65–74.

Newman, Joseph W. and Richard Staelin (1972), "Prepurchase Information Seeking for New Cars and Major Household Appliances," *Journal of Marketing Research*, 9, (August), 249–57.

Painton, Scott and James W. Gentry (1985), "Another Look at the Impact of Information Presentation Format," *Journal of Consumer Research*, 12 (September), 240–44.

Payne, John W. (1982), "Contingent Decision Behavior," *Psychological Bulletin*, 92 (2), 382–402.

——— (1992), "Behavioral Decision Research: A Constructive Processing Perspective," *Annual Review of Psychology*, 43, 87–131.

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

Punj, Girish N. and Richard Staelin (1983), "A Model of Consumer Information Search Behavior for New Automobiles," *Journal of Consumer Research*, 9 (March), 366–80.

Ratchford, Brian T. (1982), "Cost-Benefit Models for Explaining Consumer Choice," *Management Science*, 28 (February), 197–211.

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

——— and Glen L. Urban (1988), "New Consumer Durable Brand Choice: Modeling Multiattribute Utility, Risk and Belief Dynamics," *Management Science*, 34 (February), 167–85.

Schkade, David A. and Eric J. Johnson (1989), "Cognitive Processes in Preference Reversals," *Organizational Behavior and Human Decision Processes*, 44 (June), 203–31.

Shugan, Steven M. (1980), "The Cost of Thinking," *Journal of Consumer Research*, 7 (September), 99–111.

Simonson, Itamar, Joel Huber, and John Payne (1988), "The Relationship Between Prior Brand Knowledge and Information Acquisition Order," *Journal of Consumer Research*, 14 (March), 566–78.

Svenson, Ola and Anne Edland (1987), "Change of Preferences Under Time Pressure: Choices and Judgements," *Scandinavian Journal of Psychology*, 28, 322–30.

Swan, John E. (1969), "Experimental Analysis of Predecision Information Seeking," *Journal of Marketing Research*, 6 (May), 192–97.

——— (1972), "Search Behavior Related to Expectations Concerning Brand Performance," *Journal of Applied Psychology*, 56 (4), 332–35.

Urban, Glen L., John R. Hauser, and John H. Roberts (1990), "Prelaunch Forecasting of New Automobiles," *Management Science*, 36 (April), 401–21.

Urbany, Joel E. (1986), "An Experimental Examination of the Economics of Information," *Journal of Consumer Research*, 13 (September), 257–71.

Weinberg, Bruce D. (1992), "An Information-Acceleration-Based Methodology for Developing Preproduction Forecasts for Durable Goods: Design, Development, and Initial Validation," Unpublished doctoral Thesis, Sloan School of Management, Massachusetts Institute of Technology.

Westbrook, Robert A. and Claes Fornell (1979), "Patterns of Information Source Usage Among Durable Goods Buyers," *Journal of Marketing Research*, 15 (August), 303–12.

Wright, Peter (1974), "The Harassed Decision Maker: Time Pressures, Distractions, and the Use of Evidence," *Journal of Applied Psychology*, 59 (5), 555–61