

**Time Flies When You're Having Fun:
How Consumers Allocate Their Time When
Evaluating Products**

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TIME FLIES WHEN YOU'RE HAVING FUN: HOW CONSUMERS ALLOCATE THEIR TIME WHEN EVALUATING PRODUCTS

ABSTRACT

We examine hypotheses on how consumers allocate their time when searching for information. Specifically, we assume that consumers maximize the value of the information subject to a budget constraint on their time. To value information consumers compare decisions with information to decisions without the information where the value of a decision is based on the expected value of the consideration set. We then relate value to purchase intent using the concept of random utility. We examine the hypotheses with data collected by a multimedia laboratory in which automobile consumers are free to choose among information from showrooms, word-of-mouth interviews, magazine articles, and advertising. They can visit any or all sources and control the amount of time they spend in each source. We model explicitly how value depends upon the time in the source and how negative information can have value. If these phenomena are included, the model fits the data and produces results that are internally consistent and face valid. We compare consumers' time allocations with the model's predictions of those allocations. We also examine an alternative model based on net-value priorities.

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 a relatively few cars. But even so her task is formidable. Because the purchase of a new car would be many times more expensive than any previous purchase 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 her academic 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 would like 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 would like 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 would like to know how to provide information that Monika will use effectively and which will affect her choice process. Naturally, we hope that 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 begin with a model which suggests that consumers use an information source as long as it is justified by the marginal value of time. We describe data collection based on an "information accelerator," a laboratory format that allows a consumer to access magazine articles, word-of-mouth interviews, and advertising, as well as "visit" a showroom, and interact with a salesperson, all in a multi-media computer environment. After examining data that bears on the model and the relevance of the information accelerator, we estimate the parameters of the model, examine their implications, and compare the predictions to observed consumer time allocations. Because many models in the literature address the choice of information source rather than the time allocated to a source, we formulate an alternative model in an attempt to address this issue. It is based on the notion that consumers go first to information sources which provide the largest net value and then search them in decreasing order of value. This alternative model is estimated and compared to observed consumer choice of information sources. We close with a discussion of future research.

INFORMATION SEARCH MODELS

Many researchers have proposed a rational cost/benefit framework (Bettman 1979, proposition 5.3iiia; Copeland 1923; Juster and Stafford 1991; Lanzetta and Kanareff 1962; Marshak 1954; Meyer 1982; Painton and Gentry 1985; Payne 1982; Punj and Staelin 1983; Ratchford 1982; Swan 1969, 1972; Urbany 1986) as an approximation to consumer decision making behavior while recognizing that the true process may be based on more-detailed, more-complex, more-heuristic behavioral rules. Their hypothesis is that much of the observed

behaviors can be explained as if they resulted from the simpler, rational process. Work on consideration set composition has applied the notion of evaluation cost to the process of adding another brand to an existing set of brands (Hauser and Wernerfelt, 1990, Roberts and Latin, 1991). In this tradition we build our model based on the information-search concept that consumers seek benefits (value) from information and that these benefits must be balanced with the cost of obtaining that information.

The Value of Information

In Monika's problem suppose we already know that she is considering the Miata; we are interested in whether she evaluates source s . If Monika gets information she will likely update her beliefs about the Miata, but she might also update her beliefs about other cars that she is considering. Neither Monika nor we know yet whether she will choose the Miata. Thus, we model the change in the value of Monika's consideration set based on the information in source s . 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 $\tilde{u}_{j,s}$, a random variable, represent Monika's beliefs about the utility of car j after searching source s and let \tilde{u}_j , 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 based on information after source s has been searched and define $E[\cdot]$ as the expected value before choosing a source to search. The value, v_s , of searching source s is then:

$$v_s = E_s[\max(\tilde{u}_{1s}, \dots, \tilde{u}_{js}, \dots, \tilde{u}_{ns})] - E[\max(\tilde{u}_1, \dots, \tilde{u}_j, \dots, \tilde{u}_n)] \quad (1)$$

Note that value can be defined either before a source is searched or after a source is searched. In the former case the mathematical expectation is based on consumer beliefs prior to information being obtained; in the latter case the expectation is based on consumer beliefs after the information is obtained. In our models we make clear whether the expectation represents beliefs before or after a source is searched.

Equation 1 makes sense when information is positive, that is, when the utilities after source s exceed those before source s . 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 it indicates that some of the cars she is considering are unsafe. Since the specific manner in which we model the value of negative information is best illustrated in the context of our data collection measures, we defer that discussion until after we describe our data.

Equation 1 (or the analogy for negative information) defines the value of the source, but this is only part of the problem. Suppose that Monika buys *Consumer Reports*. She can spend five minutes and just examine the ratings of the Miata (and competitive cars) or she can spend an hour studying every aspect of the report and how it relates to her. Perhaps the value of *Consumer Reports* in her decision problem is greater in the latter case than in the former case? If this is true then we must model value as a function of the time Monika allocates to a source. Monika's problem is now more difficult. Not only must she decide which sources to search, but she must decide how much time to spend searching each source. Monika must decide whether the extra half hour at the dealer or the extra half hour talking to colleagues about her forthcoming purchase is worth the time taken from research and teaching.

The Allocation of Time

To model Monika's time-allocation problem we define t_s as the time spent in source s and allow v_s to depend upon t_s . We also 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 Miata 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 upon the value of the research (to her), v_s , the value of learning about the Miata from various sources, v_s 's, and the time she allocates to the tasks, t_s and t_o 's.

We formalize Monika's time-allocation as an attempt to maximize value subject to a budget constraint on time. (Equation 2 is an example of the general class of time allocation problems reviewed in Juster and Stafford 1991.)

$$\begin{aligned} \max \quad & \sum_{s=1}^S v_s(t_s) + v_o(t_o) \\ \text{s. t.} \quad & \sum_{s=1}^S t_s + t_o = T \end{aligned} \tag{2}$$

Before we address the solution to the time-allocation model we must make one more decision. One way for Monika to address the problem is to sit down at the beginning of the

weekend and allocate her time, in essence budgeting time among visiting dealers and working on her research. Another way for Monika to address the problem is to visit the Miata dealer and decide while talking to the salesperson when to leave. In reality, Monika probably does a little of both. For our formal model we assume that somehow, based on her prior expectations, Monika knows which sources are worth visiting, 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 returns¹. For example, we assume that Monika gets more information in the first hour at the dealer than she does in the second hour at the dealer.

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 assume Monika computes this (marginal) value as she receives information from the source. We observe the value after she exits the source. Later in this paper we attempt to model the choice of source, however our first model, time allocation, focuses primarily on the exit decision.

Equation 2 is a separable concave optimization problem. Its solution is simple². For each source:

$$\begin{aligned} & \text{Either } t_s = 0 \\ & \text{or} \\ & \frac{\partial v_s}{\partial t_s} = V_o = \text{marginal value of free time} \end{aligned} \tag{3}$$

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. On the other hand, Monika will allocate time to the source up to the point where she can get more value from spending time elsewhere. For example, Monika may intuit that one hour at a Miata dealer is justified, but while she is at the dealer she decides 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.

¹Technically we need only that the function is concave after an initial s-shape threshold. Indeed, we use such a function in our estimation.

²Ratchford (1982) formulates a similar, but subtly slightly different, model. Ratchford 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 upon the information that is obtained, then we obtain the same marginality conditions as equation 3.

Costs other than Time

While Monika may obtain *Consumer Reports* from her university's library, she might find it more convenient to purchase it at a news stand. When she visits a dealer she has to pay transportation costs (bus fare or gas). Etc. In general, we can 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 2. 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 Miata 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 upon the sources that she searches prior to searching that source. Thus, when we parameterize our model we allow the value function to depend upon "history," that is, upon the sources that have already been visited. We indicate the dependence upon history with a subscript, h . Naturally, to implement our model we must represent $v_{sh}(t_s)$ by a parameterized function and estimate the parameters of the function based on observed search behavior. We address the specific parameterization after we describe our data.

DATA COLLECTION AND INFORMATION ACCELERATION

There are a number of ways to examine our hypotheses about how consumers allocate time when evaluating products. 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 such informal qualitative experience forms the basis of our hypotheses. For this paper we choose a laboratory technique known as "information acceleration³." It is similar to the spirit of revealed preference in economics and is related to data collection via Mouselab (Johnson, Payne, and Bettman 1988, Johnson, et. al. 1986, Johnson and Schkade 1989, Payne, Bettman and Johnson 1988), Search Monitor (Brucks 1988), Computer Laboratory (Burke, et. al. 1991), and other computer simulators (Meyer and Sathi 1985, Painton and Gentry 1985, Urbany 1986) for behavioral decision theory experiments.

³The term was coined in a new-product prelaunch forecasting context to represent the concept that (1) we can observe in a couple of hours an information-search process that would normally take many weeks and (2) make available to consumers information that they will get in the future (prototype cars, advertising, etc.). See Urban, Hauser, and Roberts (1990) for a statement of the managerial problem and a review of alternative approaches to prelaunch forecasting.

These are, in turn, evolutions of the information display board experiments (Jacoby, Chestnut and Fisher 1978, Painton and Gentry 1985).

An information accelerator is a multimedia personal computer⁴. Visual and verbal information is stored on a video disk. 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 as little time as she wants examining the articles. The computer records all input and records the time at which the consumer began and ended each activity. In our accelerator we had the following information available.

Advertisements The consumer could view actual magazine, newspaper, and/or TV advertisements on the monitor. (Driven from the video disk the monitor becomes a television screen.)

Interviews The consumer could view video tapes of unrehearsed interviews of actual consumers⁵. 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 wants.

Articles Articles designed to simulate consumer information journals like *Consumer Reports* and other trade publications, e.g., *Road & Track*, are 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, a manufacturer's price sticker, and a manufacturer's 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 that she is walking around the car. If she approaches the car

⁴The measures in this paper used a MacIntosh II computer, with a Mitsubishi Multisync 14" video monitor, a Truvision New Vista video card, and a Pioneer 4200 laser video disk. The software was written in Macromind Director. A videotape illustrating the information accelerator is available from the authors.

⁵After much experimentation and experience (Urban, Hauser, Roberts 1990) we have found that the most realistic word-of-mouth videos appear to be those given by either unrehearsed and unscripted consumers or professional improvisational actors. However, we do provide the general topics and information they are to cover. Videotaping was done by a professional production company.

door, she is given the option of opening the door 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 the manufacturer's brochure.

The advertisement, interview, article, and showroom information were chosen, based on 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, and Westbrook and Fornell 1979) as representative of the types of information that consumers access in their search for information about automobiles. The information accelerator is not limited to these sources.

From a data collection viewpoint the important characteristics of the information accelerator 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 which tell her how long respondents typically spend in a source.

Context and Sample

In this paper we examine data from an information-acceleration project conducted to test consumer reaction to a new two-seated sporty car, the Buick Reatta convertible, developed by General Motors. 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 was 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. While we expect consumer preferences for the Reatta and the RX-7 to differ, we hope that the process by which consumers search for information does not. To the extent that sample sizes allowed comparisons, we found no significant differences in the information-search processes.

In addition to forecasting sales of the Reatta, we tested the ability of the information accelerator to reproduce an actual showroom. Thus, 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. The visit was timed.

For external validity of the forecast and to assure that consumers would have an interest in information on the Reatta and the RX-7, consumers were prescreened (via 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 twenty-five dollar 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 as follows:

Reatta, computer showroom	71
Reatta, actual showroom	43
RX-7, computer showroom	40
RX-7, actual showroom	23

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 via thermometer scale with the eleven verbal anchors which are commonly used in purchase intent scales (Juster 1966). See figure 1. The consumer provides a 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 based on a picture of the target car. The final measure is taken after the consumer indicates that she is done searching for information.

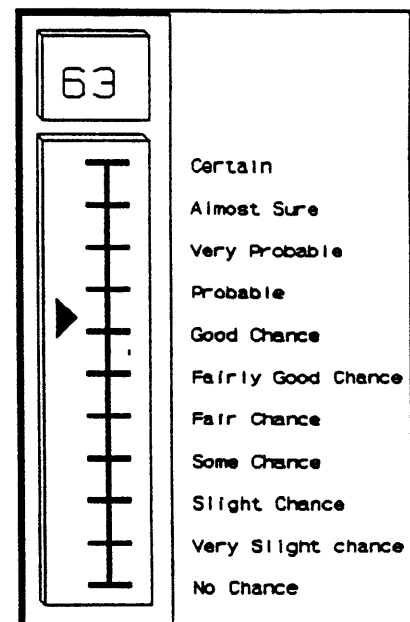


Figure 1: Measure of Purchase Intent

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 Juster (1966), McNeil (1974), Morrison (1979), and Kalwani and Silk (1983)). In our theoretical development we refer to purchase probabilities; in our empirical work we use purchase intent measures and assume that they are monotonically increasing in purchase probabilities.

Purchase probabilities relate to the perceived utility of a brand because the probability that a consumer purchases brand b , $p_s(b)$, is the probability that brand b is the brand that maximizes the consumer's utility. That is,

$$p_s(b) = \text{Prob}[\check{u}_{bs} \geq \max(\check{u}_{1s}, \dots, \check{u}_{b-1,s}, \check{u}_{b+1,s}, \dots, \check{u}_{ns})] \quad (4)$$

The s subscript indicates that the probability is the consumer's best guess given the information up to and including source s . We assume that the consumer realizes that the probability may change as more information becomes available.

Information about a brand can change that brand's purchase probability in many ways. If the information is positive it can increase the consumer's perception of the mean utility. This will increase the purchase probability. Similarly, negative information will decrease the purchase probability. But information can also reduce risk by decreasing the consumer's uncertainty. Decreased risk means increased purchase probability. Thus, information which decreases risk will also increase the purchase probability. (For example, see Meyer 1982, Meyer and Sathi 1985, and Roberts and Urban 1988.) Finally, information can affect the utilities of other brands and, by implication, affect brand b 's purchase probability.

We have not yet specified how purchase probabilities relate to the value of an information source. This is a complex question which we attempt to address in later sections.

Budget Constraint on Time

It is less costly to search for information with the accelerator 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 accelerator. 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 which 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. Based on these answers they were designated low, medium, and high searchers with allocations of 7, 10, and 13 minutes in the accelerator. 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 accelerator so that consumers searched the same number of sources in the accelerator as they did 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 accelerator was within a standard deviation of the number of sources that consumers reported. For example, on average consumers searched 2.41 sources in the accelerator and indicated (prior to the accelerator) that they searched 2.46 sources when gathering information for an automobile purchase.

The Accelerator as a Representation of Information-Search Behavior

By design consumers can search for information faster in the accelerator than they can otherwise. Furthermore, this acceleration can vary by source. For example, a showroom visit might take a few hours for Monika, but only a few minutes in the accelerator. On the other hand, the acceleration of the time it takes her to read *Consumer Reports* might be less dramatic. Thus, it would be dangerous to project from the accelerator the relative amount of time consumers spend in each source.

However, the various information sources made available in the accelerator are still information sources. The consumer faces a binding budget constraint on her time and thus faces a time-allocation 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 accelerator 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 by the computer or a short walk to an actual mock-up of a showroom. Thus, as long as we limit our analyses to the allocation of time *within* the accelerator and make no attempt to compare accelerated time to actual time, we should be able to examine the theory developed in this paper. The hints at realism (figures 2 and 3 and the external comparison with the number of sources) only serve to make us more comfortable with the data.

SOME CHARACTERISTICS OF THE DATA

Purchase Intent Measures

Treatment Effects. If the purchase intent measures are used for prelaunch forecasting we expect that they would distinguish between the Reatta and the RX-7. At minimum, if the

accelerator is to represent information search we expect that the difference between the cars should be much larger than the difference between the video showroom and the real showroom. Two measures are relevant for comparing the experimental treatment effects: (1) the final purchase probabilities measured at the end of the accelerator and (2) the change in purchase probability as a result of visiting either the video showroom or the real showroom. Figure 2 indicates that both measures distinguish among cars (Reatta vs. RX-7) but that there is no significant difference between the video showroom and the real showroom. (The real showroom is lower, but this is not significant.) See table 1 for the analyses of variance.

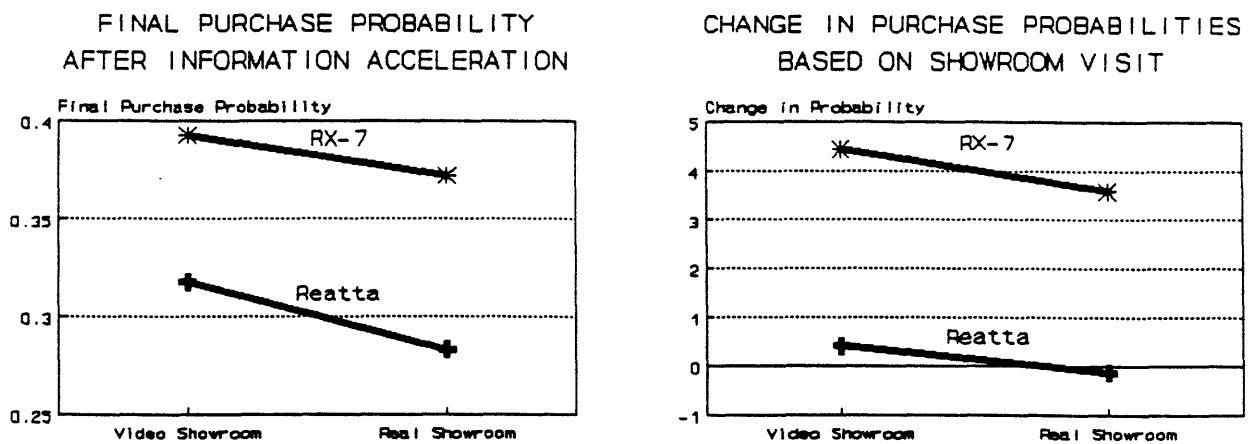


Figure 2: Comparing the Effects of Reatta vs. RX-7 and Video vs. Real

SOURCE OF VARIATION	FINAL PROBABILITY			CHANGE IN PROBABILITY		
	D.F.	MEAN SQ.	F-STAT.	D.F.	MEAN SQ.	F-STAT.
Main Effects						
Video vs. Real	1	144.3	0.22	1	10.4	0.05
Reatta vs. RX-7	1	2835.1	4.33	1	653.8	2.96
Interaction	1	392.7	0.60	1	0.1	0.00
Residual	171	655.4	-	173	220.8	-

Table 1: Analyses of Variance

While figure 2 does not guarantee the external validity of the purchase intent measures nor does it guarantee that the information accelerator is a true representation of the available information on the Reatta and the RX-7, figure 2 does give us confidence that data from the information accelerator bears some resemblance to actual consumer information search. In subsequent discussion when the statistical results do not vary by treatment (Reatta vs. RX-7 or computer vs. showroom) we report only the single equation. If significant and relevant differences occur, they are so noted.

Decrease in variance. Because the initial measure of purchase intent is based only on a picture of the target car, we expect that the consumer's beliefs will have a large component of uncertainty. As consumers receive information we expect that they will update their purchase intent estimates and that these estimates will contain less error. Naturally consumers' tastes vary, so even at the end of the accelerator we expect consumers to vary in their purchase intentions. But we hope that the "error variance" decreases with information leaving only that component of variation that is due to heterogeneity in tastes. Figure 3 plots the variance in purchase (intent) probabilities as a function of the number of sources searched.

Notice that even at the end of (at most) six sources there is variation in purchase intent, however, this variation does decrease as more sources are searched.

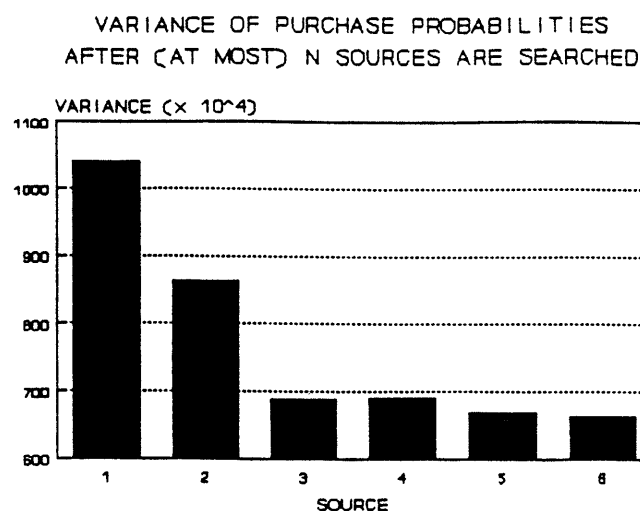


Figure 3: Decrease in Variance

Up vs. down. Initial purchase intent is a random variable as is the consumer's "true" purchase intent. Thus, as the consumer receives information it is possible that the purchase probability goes up (initial expectations are pessimistic and improved by information) or down (initial expectations are optimistic and clarified by information). From this perspective the randomness of initial expectations and the randomness of consumer tastes means that increases should balance decreases. On the other hand, the impact of information on reducing uncertainty and, hence, risk, should always increase purchase probabilities (review Roberts and Urban 1988). Thus, on balance we expect that more consumers should increase their reported purchase probabilities from the beginning to the end of the accelerator than should decrease their reported probabilities. Of those that change probabilities, 60% of the consumers increase their probabilities. Although this can not be distinguished from a demand effect⁶, at least the data are consistent with our expectations that information reduces risk.

Monotonicity. Because of heterogeneity some consumers will increase their probabilities from the beginning to the end of the accelerator and some will decrease their probabilities. Furthermore, we can imagine a consumer who gets positive information from the showroom visit then gets negative information from the word-of-mouth interviews. It is perfectly consistent with the theory if purchase probabilities oscillate. However, if too much oscillation occurs, then we

⁶The demand effect, if it occurs, should not vary by information source. Consumers are free to choose their sources and no cues are given that any source is superior to the others. Thus, for the purposes of this paper, which compares information sources, the demand effect does not affect the *comparison* of information sources. For the prelaunch forecasting task, the test vs. control car design attempts to correct for the demand effect.

would suspect either that there is too much noise in the data or that the sources were not giving accurate information. In our data, among consumers who change their probabilities, 84% of the patterns are monotonic, either all up or all down.

Search Behavior

Table 2 summarizes the selections that 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 the sources, and the time spent in each source. Table 2 also summarizes the average amount by which consumers changed their purchase probabilities based on the source. Because some consumers increased their probabilities and some decreased their probabilities, we also report the average absolute change. (We argue later that the absolute change is monotonic in value.)

It is interesting that the percent of time a source is selected first, the percent of consumers selecting a source, the time spent in a source, and the average change in purchase probabilities are clearly related. Hopefully, the models that we develop are consistent with this simple look at the data. It is also gratifying that the percent of times that consumers use a source in the information accelerator is related to the percent of times that they use that source when they are searching for information on new cars without the accelerator.

Table 2 suggests that the showroom is the most valuable source. When we estimate more complex models we will compare the parameter estimates to this observation on the unadjusted averages.

SOURCE	FIRST SOURCE	PERCENT USING	PRIOR USE	TIME IN SOURCE	CHANGE IN PROB.	ABSOLUTE CHANGE
Showroom	48%	81%	77%	174"	0.036	0.084
Interview	19%	61%	53%	157"	0.028	0.040
Articles	24%	65%	69%	107"	0.013	0.050
Advertise.	9%	38%	42%	51"	0.016	0.016

Table 2: Search Behavior -- Average Results

TIME ALLOCATION MODEL

We now choose a specific functional form for the value function, suggest one measure of value, suggest one means to model the value of negative information, and estimate the resulting model with data collected in the information accelerator.

Value of Information as a Function of Time in a Source

Intuitively, we expect the value function to have two properties. First, we expect that once a consumer is in a source she experiences decreasing marginal returns, that is, she gets more information in the beginning of her stay than at the end. Second, we expect that there will be some threshold effect, some time cost of entering a source. For example, if Monika seeks information from a Miata showroom she needs to drive to that showroom. For her, value begins only after she has reached the showroom. Analytically, this means that there is some threshold time, τ_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 τ_s seconds in the source⁷. These properties are illustrated in figure 4.

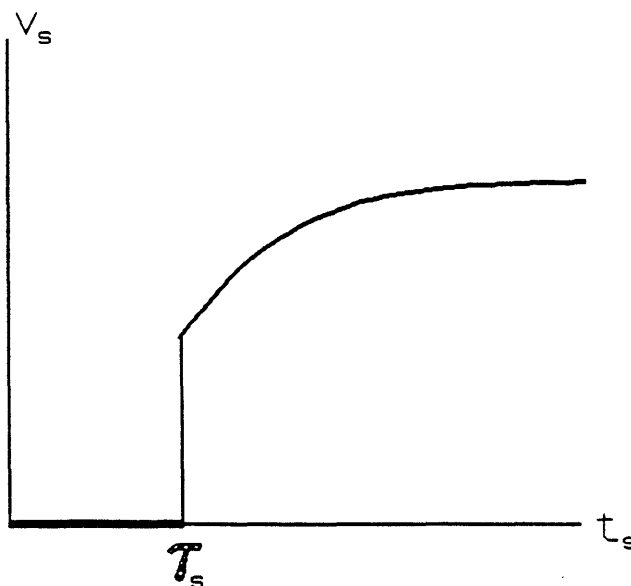


Figure 4: Value of Information as a Function of Time

One function that satisfies these properties is the $\log(\cdot)$ function. It exhibits decreasing marginal returns and is used often to measure perceptual value, e.g., decibels is a $\log(\cdot)$ function of sound amplitude. When we add a threshold, the chosen function is 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 based on history, h . This allows the value of one source, say the showroom, to depend upon whether another source, say articles, has been searched.

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

⁷Because the consumer can always choose to ignore information, the value she obtains from an accurate source is never negative. That is, we assume that negative information, such as "the transmission breaks down after 20,000 miles," provides some positive value. Note that this does not address the issue that a salesperson can give false information that is misleading and therefore of negative value. Such information is not given in the accelerator, hence the assumption of non-negative value clearly applies to our data. But applications beyond the accelerator may need to address this point. Finally, note that although the value of the source is assumed positive, the net value can be negative if the cost exceeds the value.

The Value of an Information Source

For positive information we represent the value of a source as the change, due to the source, in the value of the consideration set. (Recall that the value of a consideration set is the expected value of the maximum of the utilities of the cars in the consideration set.) As shown in appendix 1 we derive an analytic expression for this value by assuming that the consumer's perceived utilities are random variables. (If the utilities are Gumbel random variables, the maximum of a set is also a Gumbel random variable. By relating this fact to the derived logit model we derive value as a function of the purchase probabilities before and after the information source.) We show further that the larger the change in perceived purchase probabilities, the larger the value of the source. That is, value is a monotonically increasing function of $\Delta p \equiv p_s(1) - p(1)$, where $p(1)$ and $p_s(1)$ are the purchase probabilities of the target car before and after the information from source s ⁸. Finally, because of the evidence cited above that larger purchase intent measures imply larger purchase probabilities, we use the increase in purchase intent as an indicator of the value of an information source.

For negative information the computation of value is more complex. When the consumer perceives that the utility of the target brand decreases, she recognizes that her 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 the consumer would have chosen according to her prior probabilities, the $p(b)$'s. But after viewing the source she realizes that she would have gotten utilities that are different than the utilities upon which she would have made her decision. That is, she would have made her decision based on the prior utilities, but she would have gotten utility based on the posterior utilities. Thus, after viewing the information, the retrospective (before-source) value of the consideration set is given by a expectation derived from the $p(b)$'s and the u_{b_s} 's. After viewing the source it is based on the $p_s(b)$'s and the u_{b_s} 's. In appendix 1 we derive one analytic expression for this expectation. We show in the appendix that, for negative information, a source is more valuable when the decrease in purchase probabilities is larger.

Putting the results for positive and negative information together, we infer that the absolute change in purchase probabilities is a reasonable measure of the value of an information source⁹.

Our decision to model value differently for positive and negative information differently has precedent in the behavioral literature. For example, Kanouse and Hanson (1972) review a number of studies which suggest that people react differently to positive information than to

⁸Lanzetta and Kanareff (1962) also propose Δp for positive information. They demonstrate that Δp is based on utility maximization arguments of Marshak (1954) and Coombs and Beardslee (1954).

⁹Other models might also yield v , that is monotonically increasing in $|\Delta p|$. Our data analysis uses only the property that $|\Delta p|$ is a proxy for v .

negative information. Similarly, in the study of gambles Kahneman and Tversky (1979) develop a theory and present evidence that losses are valued differently than gains¹⁰. On the other hand, Russo and Schoemaker (1989) caution that decision makers often ignore negative information.

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 logarithm of the time in the source (this gives us the b_{sh} 's). The data is based on 351 total sources that the consumers searched with the information accelerator¹¹.

In none of the regressions were the a_{sh} 's significant. For example, for the second set of regressions (described below) the comparison between a regression with the a_{sh} 's and without the a_{sh} 's resulted in no significant improvement ($F(7,336) = 0.453$).

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 set of regressions, 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 ($F(4,343) = 6.34$). 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. ($F(8,335) = 0.853$). Thus, the best regression (of the regressions that we ran) models history by first source vs. subsequent source. It includes the b_{sh} 's and an overall constant, but not the a_{sh} 's. See table 3.

The regression in table 3 is encouraging. The results in table 3 have *post facto* face validity. It is reasonable, based on 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 source chosen. The regression is significant as are most of the coefficients. All of the coefficients have the proper sign. If we compare table 3 with the average results in table 2, we see that the information source with the largest coefficient is the source that is chosen most often and chosen first most often. It is also the source in which consumers spend the most time.

¹⁰Our theory uses traditional utility functions rather than prospect-theory utility functions. However, future research might modify our equations with prospect-theory utility functions.

¹¹Our analysis is based on 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 the accelerator. Value can not be measured for the flat-liners. Naturally, when flat-liners are included in the regression we get the same relative results, but with smaller coefficients.

VARIABLE	ESTIMATE	t-VALUE
Showroom as a first source	3.3*	5.8
Showroom as a subsequent source	1.8*	3.1
Interviews as a first source	1.9*	2.8
Interviews as a subsequent source	0.8+	1.4
Articles as a first source	1.9*	2.8
Articles a subsequent source	1.4*	2.1
Advertisements as a first source	1.3#	1.3
Advertisements as a subsequent source	0.5	0.6
STATISTICS		
F-statistic	10.8	
Multiple R	0.45	
Adjusted R ²	0.18	
Significance:	* = 0.05, + = 0.10, # = 0.15	

Table 3: Regression of Value on Log Time

Implied Time Allocation

To develop an independent test of the theory we examine the implications of the optimality conditions, equation 3. 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 value of information, $\partial v_{sh}/\partial t_s$, equals the marginal value of free time, V_o . For the logarithmic function in equation 5 this implies that $t_s = b_{sh}/V_o$ for all sources. Because we do not estimate V_o and because we expect it to vary across consumers, we derive¹² equation 6 as a condition that does not depend upon this unknown parameter.

$$\frac{t_s}{\sum_{s=1}^S t_s} = \frac{b_{sh}}{\sum_{s=1}^S b_{sh}} \tag{6}$$

Equation 6 is an independent test because, although it is implied by the theory, there is no guarantee that the regression will select coefficients such that equation 6 is satisfied. The

¹²Divide both sides by $\sum_{s=1}^S t_s$, substitute b_{sh}/V_o for t_s on the right-hand side of the equation. V_o cancels out.

regression relates value (the absolute change in intent measures) to time in a source whereas equation 6 relates the ratio of the estimates to the ratio of time. It is quite easy to construct an example where the regression has a perfect fit and equation 6 is not satisfied. For simplicity of exposition, define R_t as the time ratio on the left hand side of equation 6 and define R_b as the ratio of the parameter estimates on the right hand side of equation 6.

To examine equation 6 we realize that although 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, say Robert, used only interviews and articles, his R_b ratio would be based on only those sources. Thus, 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 shown in table 4. The correlation of the four averages is very high at 0.94. The more realistic test is the correlation across consumers which is a respectable 0.70¹³.

SOURCE	R_t -RATIO	R_b -RATIO
Showroom	0.53	0.51
Interviews	0.22	0.32
Articles	0.31	0.25
Advertisements	0.14	0.12
Correlation (of averages)		0.94
Correlation (by consumer)		0.70

Table 4: Comparison of R_b Ratios and Predicted Time Allocations

Based on tables 2 through 4 we conclude that our model has reasonable face validity, fits the data acceptably, and predicts time allocations well. Based on this data we believe that the hypotheses of the model are worth consideration as explanations of how consumers allocate their time among information sources.

NET-VALUE PRIORITY MODEL

A key aspect of the time-allocation model is that time is modeled as an endogenous variable rather than as a cost. One can also model time as a cost and posit that consumers choose sources based on net value, n_s . Net value is the value of an information source minus the cost of that information source, that is, $n_s = v_s - c_s$, where the cost, c_s , includes time costs, thinking costs, and other costs. This model has been applied successfully in the literature by Bettman 1979, Brucks 1988, Coombs and Beardslee 1954, Lanzetta and Kanareff 1962, Marshak 1954, Meyer 1982, Painton and Gentry 1985, Punj and Staelin 1983, Shugan 1980, Swan 1969, and Urbany 1986.

¹³One might argue that the correlations in table 4 are optimistic because there is a constraint that the ratios add to 1.0 and because a small fraction of consumers consider only one source. Eliminating one source per consumer and eliminating consumers with only one source still gives a respectable correlation of 0.52.

The basic idea of such a model is that consumers solve the optimization problem in equation 2 by going first to the information source that provides the highest net value, then to the next highest value source, etc. This model can be derived from equation 2 if we assume that the difference between the values of the sources is large relative to the difference in the value that is gained by spending t_s (say 10 minutes) rather than t'_s (say 5 minutes) at the source. For example, Monika might know that she will spend at least two hours at Mia's Miata, but doubts whether spending two and one-half rather than two hours will change dramatically the value of her visit.

If the value of a source, v_s , is independent of t_s , the general time allocation problem in equation 2 becomes a knapsack problem. Under most circumstances¹⁴, the simplest and most direct solution is either the primal or the dual "greedy" algorithm (Gass 1969, Cornuejols, Fisher and Nemhauser 1977, Fisher 1980). In the primal algorithm the consumer chooses sources in the order of v_s/t_s as long as v_s/t_s is greater than the marginal value of time, V_o . Equivalently, the consumer can solve the dual mathematical program and choose sources in the order of $v_s - V_o t_s$. If the value of the source is defined net of all costs other than time, then this solution implies that consumers choose sources in the order of the net value. (See Hauser and Urban [1986] for discussion and empirical data on the use of the greedy algorithms, both primal and dual, as approximations to consumer monetary budget allocations. We choose the dual algorithm based on the better fits in their 1986 data.)

To implement the net-value priority model we derive a model, similar to that derived by Meyer (1982), which is analogous to random utility choice models such as the logit model (Ben-Akiva and Lerman 1985). In particular, we assume that we, as observers of the consumer, can never measure net value perfectly. This means that net value, $\tilde{\pi}_s$, is a random variable. Because the net values of each source are random variables, we can not predict perfectly which source the consumer will choose. Instead, we predict the probability, P_s , that source s will be chosen next. This probability is defined by:

$$P_s = \text{Prob} [\tilde{\pi}_s \geq \tilde{\pi}_1, \tilde{\pi}_2, \dots, \tilde{\pi}_{s-1}, \tilde{\pi}_{s+1}, \dots, \tilde{\pi}_S] \quad (7)$$

We define value based on the difference in the value of the consideration set before and after information. (Review equation 1.) However, we allow value to remain a random variable and do not take the expected value. Net value is value minus costs¹⁵. In symbols,

¹⁴The greedy algorithm provides an exact optimum if sources are not integral. In most cases it is exact if $v_o(t_o)$ is continuous and the v_s and t_s are not extreme. In other cases it provides an excellent approximation to the optimum. As in our previous papers we argue that the simpler greedy algorithm is more likely to approximate consumer behavior than the very complex mixed integer programs. The shadow price, V_o , is defined for the optimal t_o .

¹⁵This equation is also a formalization of ideas expressed by personal communication from Ward Edwards to Lanzetta and Kanareff (1962, footnote 2, p. 460).

$$\tilde{\pi}_s = \max(\tilde{u}_{1s}, \dots, \tilde{u}_{js}, \dots, \tilde{u}_{ns}) - \max(\tilde{u}_{1.}, \dots, \tilde{u}_{j.}, \dots, \tilde{u}_{n.}) - c_s \quad (8)$$

where c_s is the cost of searching source s .

Equation 8 does present a conceptual challenge. The posterior utilities, \tilde{u}_{js} , are defined based on the information the consumer obtains from source s . But the net-value priority model attempts to model the decision by the consumer to search source s before the posterior utilities are observed. This means that the consumer must make her decision based on the net value she *expects* to get from the source, not the net value she actually obtains from the source. Thus, in order to apply the model to our data, we must assume that, on average, the consumer gets what she expects and that any variation is a zero-mean random variable. (This conceptual problem did not apply to the time-allocation model because the time-allocation model represented the consumer's decision to exit the source rather than to enter the source.)

To make the model practical we make the same assumption that is used to derive the logit model; we assume that the utilities are independently distributed such that the $\tilde{u}_{.s}$'s and the \tilde{u}_{bs} 's are equal to some observed utility plus an error that is Gumbel distributed. The formal derivation is in appendix 2. The sketch of the proof is as follows. The Gumbel-distributed errors imply a logit model for choice probabilities. We use this implied logit model to relate the deterministic components of the utilities to the observed purchase probabilities. Then with the assumption of Gumbel-distributed errors and equation 8 we derive the distribution of net value. Putting it all together gives an expression for P_s as a function of the purchase probabilities and the search costs. For simplicity we do not repeat the equation here, but it is intuitive in the sense that the consumer is more likely to choose a source if $p_s(b)$ is larger, if $p_s(b)$ is smaller, and if c_s is smaller.

With an analytical expression for the model and observations of the order in which each individual chooses sources, we use maximum-likelihood estimation to estimate the implied costs and perceived values of the sources. Specifically, we specify the cost of searching a source s as a function of the time in the source (e.g., Bettman 1979, Brucks 1988, Juster and Stafford 1991, Meyer 1982, Painton and Gentry 1985, Punj and Staelin 1983, Urbany 1986) and the number of sources left to search (Meyer 1982, Shugan 1980). See equation 9.

$$c_s = \beta_1 t_s + \beta_2 m_s \quad (9)$$

$$u_{1s} = u_{1.} + \theta_s$$

In equation 9, t_s is the time in source s , m_s is the number of sources left to search, and the β 's are parameters to be estimated. (The number of sources left to search is a proxy for the thinking cost of deciding among the sources. If it has any effect at all its effect would be on the consumer's decision to stop searching.) On the value side of the equation θ_s represents the increase in the utility of the target brand that the consumer hopes to get by searching source s .

The θ_s 's are parameters to be estimated. (u_{1s} and u_{2s} are the observable components of the utilities of the target brand before and after searching the source.)

Equation A9 is nonlinear, but we can estimate the unknown parameters, β_1 , β_2 , and θ_s 's, with a nonlinear maximum-likelihood estimation package. The resulting estimates are given in table 5.

The results are disappointing. Neither the cost of time nor the cost of thinking is significant. Even if significance were disregarded they are both negative! If the negative signs are to be believed, the more time a consumer spends in a source the less costly the source. Furthermore, articles have negative value while the showroom appears to have little value ($\theta_1=0.01$) even though it is chosen first most often and is chosen by the largest percentage of consumers (table 2).

PARAMETER	ESTIMATE	t-VALUE
Cost of Time (β_1)	-3.76	-0.51
Thinking Cost (β_2)	-0.04	-0.05
Source Values		
Showroom (θ_1)	0.01	0.02
Interviews (θ_2)	0.33	2.21
Articles (θ_3)	-0.38	-2.13
Advertise. (θ_4)	0.11	1.12
STATISTICS		
Log Likelihood	-710.2	
Chi-squared (signif.)	13.1 (0.01)	

Table 5: Maximum-Likelihood Estimates for Net-Value Priority Model

To understand why the quantal choice model would give such estimates, we note in table 2 that consumers appear to spend more time in the sources that they choose first (and more often). Such a correlation would lead to a negative coefficient on time. If time is related to value (as in equation 5), this coefficient would capture part of the value component and the residual (due to the θ_s 's) might be misleading. The disappointing results of table 5 are probably due to more than technical problems with the estimation. Omitting the endogenous element of active search may be one cause of the non-intuitive estimates.

Because Meyer (1982) obtains support for a theory based on a similar quantal choice model, we examine the differences in the measurements. Meyer (1982) formulates both value and cost components in his model, but his experiments test only the value component. The key difference in the information accelerator is that consumers choose the time in a source; thus *both value and cost* are dependent upon this chosen time. The quantal choice model formulation of the net value priority model models only cost as a function of the chosen time, not value.¹⁶

Although the net-value priority model does not model the endogeneity of time, we report the estimation in this paper because we believe that valuable knowledge is gained from failed modeling attempts. The derivation in appendix 2 makes use of powerful (and popular) quantal-

¹⁶Interestingly, when Urbany (1986) manipulates search cost and value (price dispersion and uncertainty) he finds an interaction between cost and value.

choice modeling technology. It is a natural way to approach the estimation problem and, had it worked, it would have paved the way for fruitful extensions. The fact that it provides a poor fit to the data while the time-allocation model provides a good fit to the data suggests that it is fruitful to study further the differences in the models. Perhaps future work will develop a formulation that can explain both the order in which sources are chosen *and* the time that is allocated to sources.

The need to model time as an endogenous variable has implications for experimental investigations of information sources. The time-allocation model recognizes that both the cost *and the value* of an information source depends upon the time in the source. Thus, had we assigned consumers to sources and not constrained (or measured) the time in the sources we would not have obtained correct measures of value. Time would have been a confounding variable, especially if the choice of time allocation was left to consumers. This realization suggests a research program which can build upon the experiments of Brucks (1988), Burnkrant (1976), and Urbany (1986).

If negative information has value, the negative information in table 5 has research value.

SUMMARY AND FUTURE DIRECTIONS

In this paper we have examined a time-allocation model in which the value of an information source depends upon the time spent in the source. In addition, the model recognizes that there can be positive value for negative information. We posit that negative information is valuable because consumers realize that without such information they would have chosen according to the prior utilities but they would have received the posterior utilities. For both positive and negative information we are able to show mathematically that the value of information is related to the absolute change in purchase intent.

The model was estimated based on data collected with an information-acceleration computer system. The information accelerator is a multi-media laboratory in which the consumer is presented with simulations of showroom visits, word-of-mouth interviews, magazine articles, and advertising. The sources are made as realistic as is feasible, but the consumer can search them in minutes rather than hours. The accelerator has some internal consistency in the sense that consumers search as many sources in the accelerator as they do in actually searching for a car and in the sense that the changes in purchase-intent measures are consistent with the concepts of risk reduction and variance reduction. In addition, from a prelaunch forecasting perspective, the difference between an accelerated showroom and a real showroom is not significant while the difference between a Reatta and an RX-7 is significant.

The data from the accelerator suggest that "value" can be related to the time in an information source and that the optimality conditions (R , *ratios*) predict consumers' allocations of time in the accelerator. The fits are encouraging.

We also estimated a net-value priority model in which the value of a source does not depend upon the time in the source. This model also differed in that it attempted to model the choice of source rather than the time in the source. Regrettably, the model did not provide intuitively appealing parameter values suggesting either (1) that it is necessary to model explicitly the dependence of value on time, (2) that consumer expectations of value do not (on average) match realizations of value, or (3) that consumers do not make the entrance decision via a net-value-priority algorithm. We present the null result of the net-value-priority estimation because we believe it is a stimulus for further investigations in this area.

Finally, we illustrate how the time-allocation model can be used to examine established results in the behavioral literature.

Future Directions

We are improving the information accelerator to provide better data and we are using the information accelerator to collect more complete data. Among the improvements we are developing are the inclusion of more information about the target car, information on cars other than the target car, information on the product line, the simulation of future scenarios via simulated television news programs, and a simulation of "a day in the life" of an owner. Our next application will be to an electric vehicle that is scheduled for introduction in 1994. In this project we are using 1994 newspaper articles to simulate different environmental-consciousness scenarios. The information accelerator also provides an information briefing which represents the common knowledge that would exist in 1994 about electrically-powered vehicles.

Among the additional data we plan to collect are changes in consumer perceptions of product attributes, changes in the variances of product attributes, and changes in utility (e.g. constant sum preferences) as the result of information. At the end of the accelerator we plan to measure the perceived value of the information. We hope to be able to develop more detailed measures so that we can infer value from the attribute changes as well as the purchase intent measures, so that we can separate risk reduction from changes in perception, and so that we can diagnose how information works through changes in the perceptions of product attributes.

The time-allocation model can be extended by exploring other formulations for the value of negative information. For example, one approach is to explore the option-value of a source in an analogy to option-values in financial markets. Although the net-value-priority model is intuitively appealing, it did not fit our data. Perhaps more-detailed data in which value is inferred from attribute changes might provide a better test of the model. The results should be interesting.

Finally, the time allocation model can be used to interpret established results in the behavioral literature. For example, Svenson and Edlund (1987) and Wright (1974) provide evidence that consumers put more weight on negative information when placed under time pressure. This result could be explained if the value function were steeper and leveled out more

rapidly for negative information. Then when the time constraint, T , is decreased, the optimality conditions imply that a greater percentage of time is allocated to negative information. It is easy to construct an analytical proof for such value functions, however such value functions are more complex than the logarithmic value functions in this paper. They would have more parameters that would need to be estimated, hence could only be tested with new data collection and/or experimental manipulations.

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Appendix 1

DERIVATION: THE VALUE OF INFORMATION vs. THE ABSOLUTE CHANGE IN PURCHASE PROBABILITIES

Follow the notation of the text. Assume that the u_{bs} 's are independently Gumbel distributed with parameters u_{bs} and μ 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, property 5), $p_s(b)$ is given by the logit model where we have subsumed the scaling parameter, μ , into the scaling of the utilities.

$$p_s(b) = \frac{e^{u_{bs}}}{\sum_{b=1}^B e^{u_{bs}}} \quad (\text{A1})$$

An analogous equation applies to $p(b)$. After gathering information from source s , the value of the consideration set is $E_s[\max(\tilde{u}_{1s}, \tilde{u}_{2s}, \dots, \tilde{u}_{ns})]$. According to properties 2 and 7 of the Gumbel distribution (Ben-Akiva and Lerman 1988, p. 105), this value is given by $\log \sum_b \exp(u_{bs}) = \log[\exp(u_{1s}) + \alpha]$ plus a constant. Similarly, prior to gathering information from a source, the value of the consideration set is $E[\max(u_{1.}, u_{2.}, \dots, u_{n.})]$ which is given by $\log[\exp(u_{1.}) + \alpha]$ plus the same constant. When the consumer 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. That is,

$$v_s = E_s[\max(\tilde{u}_{1s}, \tilde{u}_{2s}, \dots, \tilde{u}_{ns})] - E[\max(u_{1.}, u_{2.}, \dots, u_{n.})] \quad (\text{A2})$$

solving equation A1 for u_{1s} , $u_{1.}$, and α , and substituting we obtain,

$$v_s = \log \left[\frac{1 - p_s(1)}{1 - p_s(1)} \right] \quad (\text{A3})$$

Let $\Delta p = p_s(1) - p(1)$. Holding $p(1)$ constant, differentiate A3 with respect to $p_s(1)$.

$$\frac{\partial v_s}{\partial p_s(1)} = \frac{1}{1 - p_s(1)} \quad (\text{A4})$$

Thus, when the consumer perceives that the utility of the target brand improves, v_s increases whenever Δp increases.

When the consumer perceives that the utility of the target brand decreases, then she recognizes that her 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 the consumer chooses according to the $p(b)$'s. But after viewing the source she realizes that she would have gotten utilities given by the u_{bs} 's. Thus, the value of the consideration set prior to viewing the source is given by an expectation derived from the $p(b)$'s and the u_{bs} 's even though the probabilities were based on her expectations for the u_{bs} 's. That is,

$$v_s = E_s[\max(\tilde{u}_{1s}, \tilde{u}_{2s}, \dots, \tilde{u}_{ns})] - \{p_s(1)E_s[\tilde{u}_{1s}] + [1-p_s(1)]E_s[\max(\tilde{u}_{2s}, \dots, \tilde{u}_{ns})]\} \quad (\text{A5})$$

Using the properties of the Gumbel distribution, $E_s[\tilde{u}_{1s}] = \log[\exp(u_{1s})]$ plus a constant. As defined above $E_s[\max(\tilde{u}_{2s}, \dots, \tilde{u}_{ns})] = \log[\alpha]$ plus the same constant. Substituting we obtain,

$$v_s = p_s(1)\{\log[1-p_s(1)] - \log p_s(1)\} - \log[1-p_s(1)] \quad (\text{A6})$$

Notice that $v_s \geq 0$ for $\Delta p < 0$. Holding $p_s(1)$ constant and differentiating we obtain,

$$\frac{\partial v_s}{\partial p_s(1)} = \frac{\Delta p}{p_s(1)[(1-p_s(1))]} \quad (\text{A7})$$

Hence, when the information is negative, $\partial v_s / \partial \Delta p < 0$ if $\Delta p < 0$. Thus, v_s increases as $|\Delta p|$ increases for negative information.

Equation A5 assumes the consumer makes a choice of either $b=1$ or $b \neq 1$, then chooses the maximum from the set. More complex models could modify the conditioning of the expectations to reflect alternative assumptions. For example, we might consider a model of the form $v_s = \sum_b p_s(b)E[\tilde{u}_{bs}] - \sum_b p_s(b)E[\tilde{u}_{bs}]$. However, intuitively we expect that $|\Delta p|$ should be monotonic in the value of an information source.

Appendix 2 PROBABILITY OF CHOOSING SOURCE S BASED ON THE NET VALUE PRIORITY MODEL

Follow the notation of Appendix 1 and make the same assumption with respect to error terms. Then $\max(\tilde{u}_{1s}, \tilde{u}_{2s}, \dots, \tilde{u}_{ns})$ is Gumbel distributed with parameters $\log \sum_b \exp(u_{bs})$ and 1. According to the dual greedy algorithm, if the consumer chooses a source, she will choose that source s that gives her the maximum net value, \tilde{n}_s , where $\tilde{n}_s = \max(\tilde{u}_{1s}, \tilde{u}_{2s}, \dots, \tilde{u}_{ns}) - \max(\tilde{u}_{1s}, \tilde{u}_{2s}, \dots, \tilde{u}_{ns}) - c_s$. Note that \tilde{n}_s is a random variable. She will choose no source if there is no positive \tilde{n}_s . Again using property 5 of the Gumbel distribution we obtain the probability, P_s , that the consumer will choose source s .

$$P_s = \frac{\sum_{b=1}^B e^{u_{bs} - c_s}}{\sum_{s=1}^S \sum_{b=1}^B e^{u_{bs} - c_s} + \sum_{b=1}^B e^{u_b}} \quad (\text{A8})$$

where u_b represents the observable component of the utility prior to selecting the source. Let $p_s(b)$ represent the corresponding choice probability.

Without loss of generality, we let $b=1$ represent the target brand. Assume that source s affects only the target brand's utility, then u_{bs} does not depend upon s for $b \neq 1$. Now solve equation A1 for u_{bs} and substitute in equation A8. This yields:

$$P_s = \frac{e^{-c_s/[1-p_s(1)]}}{\sum_{s=1}^S e^{-c_s/[1-p_s(1)]} + 1/[1-p(1)]} \quad (\text{A9})$$

From the chosen source we observe $p_s(1)$. To estimate the model we specify c_s and $p_s(1)$ for other sources. Specifically, we let $c_s = \beta_1 t_s + \beta_2 m_s$, where t_s is the time in source s and m_s is the number of sources left to search. We specify $u_{1s} = u_{1s} + \theta_s$. Substituting known quantities we get the following equation for the chosen sources,

$$\theta_s = \log \left\{ \frac{p_s(1)[1-p(1)]}{p(1)[1-p_s(1)]} \right\} \quad (\text{A10})$$

We estimate equation A10 by we assuming that the consumers' expectations of θ_s are, on average, realized.