The Role of Preference Discovery in Consumer Search

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Abstract

This research focuses on consumers who do not have well-formed preferences. As they search and evaluate potential products, they may become exposed to previously unconsidered attributes, and incorporate them into their decision criteria. We model this phenomenon by allowing the consumer to change the weights she assigns to different attributes during the course of search. In a laboratory experiment, we elicit participants’ preferences before and after evaluating several example products, and find that 53% of participants revise their decision criteria after product evaluation. We show analytically and in Monte Carlo simulation experiments that, when considering the ultimate search outcome, it may be better to recommend and inferior product, but one that helps the consumer discover his preferences. This is because product recommendations influence the consumer’s future search path, beyond just the recommended product itself: if a product exposes the consumer to a new, previously undiscovered attribute, the consumer may shift his search to a new part of the product space. Further, providing detailed product information to consumers who do not have well-formed preferences may lead them to make suboptimal decisions. For consumers who know their preferences, more detailed product information is better.

Keywords: Revising decision criteria, Product recommendations, Probability models, Decision making under uncertainty, Multi-attribute choice models
1. Introduction

Consider the following three examples of consumer search:

*Example 1:* Amy and Bob were first time parents, and novices in hiring nannies. Initially they thought that the most important attribute was experience with daycare or with a previous family. They contacted daycare centers and colleagues whose children had grown. As they searched, they came to value experience less and empathy more. In the end they realized that a willingness to help with nominal household chores was a make or break attribute, because it gave them more quality time with their children. Household chores played no role whatsoever in their early search.

*Example 2:* Candace and Dave were moving to a new city. They wanted three bedrooms, two bathrooms, a good school district, and also valued hardwood floors, adequate lighting, and proximity to work. One home they visited had a playground across the street, and they realized how convenient this feature would be for them. After that, they began checking for playgrounds near homes they considered before visiting them.

*Example 3:* Evan is a high school student beginning his college search. Initially, he only looked at colleges with high academic ratings that were nearby, as well as colleges that are well known for their athletics teams. On one visit, Evan learned that the college had an organized program for undergraduate students to get involved in research with faculty. Prior to the visit, Evan was not even aware that undergraduate research programs were a possibility. After seeing it, Evan realized this attribute was important to him, so it became a factor in his subsequent search. While Evan was well informed about the attributes he searched, he did not realize that other attributes would be more important.

The common thread in all these examples is that novice consumers revise their decision criteria during search as they discover new attributes. Preference discovery has been long recognized in consumer behavior (e.g. Payne, Bettman and Johnson 1993, Simonson 2008). Changes in consumer decision criteria are also intuitively understood by those tasked with making recommendations to consumers. A recent *New York Times* article on real estate buyer behavior by Rogers (2013, page F4) describes a novice consumer’s search for a home: “Often people don’t know what they want. […] You may think you want X, but if you’re shown Y, you may love Y better than you ever loved X. […] Even (or especially) in these days of consumer online access, some of an agent’s value lies in her being able to offer a buyer a choice different
from his preconception.” Similarly, college counselors often suggest that “students look at schools of various types for the express purpose of helping them refine their thinking about what they want” (personal communication, November 2012). The director of a large childcare agency notes a similar pattern in parents’ preferences for nannies: “We find that parents spend a lot of energy focused on attributes of a caregiver, like college education or CPR training, which have no real correlation to how good of a caregiver someone will actually be. They learn, after being presented and disappointed in their ‘perfect candidate’ multiple times, that their focus should be on finding someone based on child rearing philosophy, temperament, and other belief systems” (personal communication, June 2014). In dating, young men and women do not always know what they will value in a potential partner, even though they usually believe they have well-formed preferences (Finkel et al 2012). Newer dating services, such as Minidates.com and CoffeeMeetsBagel.com offer blind dates to encourage real-life interaction so that daters learn what really matters in a mate (Cook, 2012). The websites claim that the final outcome is better than it would have been if daters had foregone the discovery process and relied instead on the attributes in online profiles.

At the same time, in the age of consumer online access, consumers are able to find accurate information on products before evaluating them. For example, in the context of real estate, a home buyer can use tools like Google Maps and find the location of nearby grocery stores, gyms, or playgrounds, as well as view the home listing on sites like Zillow or Trulia. There is an underlying assumption that the more precise, detailed information consumers have about their options the better they will be able to make decisions. However, we show that this may not be the case if consumers have poorly-formed preferences. With less accurate information about their options, consumers are forced to search more broadly, which helps them discover preferences and ultimately find better products.

Given these considerations, we propose a model in which consumers can discover their preferences by evaluating products and revise their decision criteria accordingly. In the proposed model, the consumer adjusts the weights she assigns to product attributes before deciding what product to evaluate next. To validate the model, we measure decision criteria experimentally, by eliciting preferences before and after the participant evaluates products. We conduct and incentive-aligned experiment to demonstrate that participants do indeed revise their decision criteria for a rental apartment after product evaluation.
In the context of this model, we study the following two questions. First, is it always better for consumers to have more detailed information about their options? Second, is a better product necessarily a better recommendation, when considering the final choice outcome?

We answer these questions using analytical results and Monte Carlo simulation studies. We show that consumers who do not have well-formed preferences are, on average, better off with noisy information about the attributes of products they have not yet examined. Consumers who know their preferences, however, achieve higher rewards if they have perfect information on all the product attributes.

A low utility product can serve as a valuable recommendation. A recommender may recommend an inferior product to help the consumer learn preferences. If recommended product exposes the consumer to initially undervalued attributes, the recommendation helps the consumer ultimately find the best product. A product recommendation can change the outcome of search not only by introducing the recommended product to the consumer’s awareness set, but also by altering the consumer’s decision criteria, which, in turn, impacts the future search path.

In the next section, we describe when preference discovery is relevant and how it relates to other consumer search behavior. We then present the model, beginning with a short review of the optimal sequential search framework. Section 5 presents the experimental evidence, Sections 6 and 7 derive implications of the model, and Section 8 suggests further research.

2. Revising Decision Criteria as a Result of Preference Discovery

Previous research has found that consumers sometimes don’t have well-formed preferences when they begin shopping for a product. First, consumer behavior researchers have studied preference learning and construction (e.g. Payne et al.1993, Simonson 2008). It has been shown that the less familiar a consumer is with the product category, the more labile her preferences are (e.g. Alba and Hutchinson 1987, Brucks 1985). Work by Greenleaf and Lehmann (1995) demonstrates that one of the reasons why consumers delay purchase decisions is the challenge of “identify[ing] the relevant set of products and product attributes to consider, and establish[ing] the importance of each attribute.” In mechanical design engineering, She and MacDonald (2013) show that offering certain “trigger features” in products increases consumers’ preference for sustainability. In movie recommendations, some work has focused on developing algorithms that provide novelty, diversity, and serendipity of recommendations (e.g. Castells et
al. 2011, Konstan et al. 2006). These papers focus on algorithms and do not explicitly model user decision making, but the quest for serendipity suggests an underlying assumption that users do not know exactly what they want. For example, seeing a recommendation for Hitchcock’s *Birds* may prompt the user to search for other horror films. This can be captured by increasing the weight of the “horror” attribute.

A consumer’s search process depends on many factors, such as the nature and complexity of the product category, the consumer’s involvement with the category, and the search environment (Bettman 1979, Moore and Lehmann 1980). We now build on their framework to develop a conceptual categorization of search and decision processes that consumers may apply, depending on the context (Figure 1).

First, we focus on products that are complex, i.e. have a large number of relevant attributes, such as cars, apartments, childcare, and college search (Box 1). If the product category has few attributes, it is easy for consumers to integrate weighted attributes to make a choice (e.g. Fishbein 1963, Green and Srinivasan 1978).

Second, we focus on high-involvement categories, such that the consumer is motivated to find the optimal product rather than apply a simple decision heuristic (Figure 1, Box 2). When making decisions about low involvement products, particularly if complex in terms of the number of attributes, integrating all the information on product attributes may require more cognitive effort than the customer is willing to expend (Wright 1975, Deshpande et al. 1982). Examples of such choices are choosing a movie on Netflix or choosing a wine from a restaurant menu: there are dozens of relevant attributes, but the decision is relatively low in importance, and consumers are likely to use a heuristic rather than engage in a long evaluation and choice process. Example heuristics include rule of thumb, variety seeking, or habit.

Third, we focus on situations when consumers are either unaware of, or fail to recall some relevant attributes (Box 3), such as in the opening examples with the playground, willingness to do housework, and programs for undergraduate research. If consumers are aware and able to recall all the relevant attributes (Box 3, Yes), then, if they also know all the attribute weights with certainty, they may also integrate the weighted attributes to choose a product (Box 4, Yes). It is also possible that consumers are aware of and recall an attribute, but have uncertainty about its weight (Box 4, No). For example, a consumer purchasing a car for the first time may be considering the possibility of purchasing a convertible, but, having never driven
1. Is the number of attributes small?

2. Are consumers highly motivated to make the right decision?

3. Are consumers aware of and able to recall all attributes of the category?

4. Are consumers aware of preference for each level of each attribute?

Consumers are exposed to new product attributes which they did not previously incorporate into their decision: PREFERENCE DISCOVERY (VIA SURPRISE)

Consumers incorporate the new decision criteria in future search: REVISION OF DECISION CRITERIA

- There is a change in attribute importance;
- Consumers are better off with less attribute information
- Product recommendations impact future search path
- There is a value to negative experiences

Consumers actively seek out information to help them resolve their uncertainty about their valuation of known attributes: ACTIVE LEARNING

Rational consumers optimally trade off EXPLORATION/EXPLOITATION

Consumers apply a heuristic to make a choice: HEURISTIC PROCESSING

Consumers integrate weighted attribute evaluations to make choice: SYSTEMATIC PROCESSING

Figure 1: Conceptual Categorization of Search Processes
one, uncertain about how she would like it. Such a consumer, who is *consciously uncertain* about the attribute’s value, would actively seek out information about the attribute (for example go to a car dealer and test drive some convertibles, or collect information from other sources) to help her resolve her uncertainty. A fully rational consumer who is consciously uncertain can act optimally, trading off exploration and exploitation. This policy requires the consumer to solve a complex attribute-based multi-armed bandit problem, which is and beyond the scope of this paper (Chapelle and Li 2011; Rusmevichientong and Tsitsiklis 2010; Scott 2010; Schwarz 2014).

Our focus phenomenon is being unaware of or failing to recall some relevant attributes (Box 3, No). For example, a novice consumer might begin searching for two-bedroom apartments in Brooklyn. Based on her beliefs about her preferences, the consumer might limit her search to Brooklyn and choose the apartments to evaluate by visiting them based on location, number of bedrooms, and condition. The consumer may be unaware of, or simply forget to consider, many other attributes, such as in-building laundry, the light from windows, wood floors, closet space, high ceiling, in-building gym, central air-conditioning, exposed brick fireplaces, the quality of the maintenance company, outdoor space, soundproof walls, proximity to supermarkets, non-clanging pipes, type of cable television available. As a result, the consumer placed little or no weight in them when choosing which apartments to visit. During the search, the consumer might see apartments with or without these attributes and change the weights she assigns to attributes. As in the opening example, seeing an apartment with a playground or a college with and undergraduate research program led the consumers to change the weights they assigned to those attributes. Or, seeing an apartment close to supermarkets, gyms, or nightclubs might cause the consumer to value those attributes more. Seeing apartments with differing levels of these attributes is serendipitous; the consumer did not choose to evaluate apartments based on these attributes because the consumer focused only on location, size, and condition. The consumer comes across these attributes in her search by surprise, discover that they are important, and, as a result, revise her decision criteria. This process is in the large solid box in the diagram.

We note that the underlying psychological processes of recalling a forgotten attribute and discovering a completely new attribute that the consumer did not know existed are different. In the opening examples, Candace and Dave knew that playgrounds existed, but failed to recall them until they saw a house with a playground. On the contrary, Evan did not even know that
undergraduate research opportunities programs existed until he visited a college that had one. Despite the difference in the process that leads to the change, the two processes are equivalent from the perspective of the choice model: both of them result in the revision of attribute weights to incorporate the new (or recalled) attribute, so we abstract away from this distinction.

For ease of exposition, we refer to consumers who are unaware of or fail to recall some attributes (Box 3, No) as novices. Novice consumers’ initial decision criteria are different from their true preferences, which are discovered upon evaluation.

3. Model Setup: Directed Sequential Search
3.1. Representing Products by Their Attributes

In order to allow for the importance of various to change during the course of search, we need a model framework of directed search in multi-attribute product space. Let \( i = 1 \) to \( I \) index the products (or services) in the market. For notational simplicity we assume finitely many products, but the basic concepts apply as \( I \) gets arbitrarily large. Each product is described by a set of attributes indexed from \( n = 1 \) to \( N \). For example, an apartment might have attributes such as rent, commute to campus, condition of apartment, closet space, air-conditioning, outdoor space, etc. In general, we allow each attribute to have discrete levels indexed by \( l = 1 \) to \( L_n \). For example, the condition of an apartment might have four levels: newly renovated throughout, renovated kitchen only, fair condition, and poor condition. For brevity, we present the utility model for all binary attributes, but we allow

\[
\mathbf{x}_i = \{x_{i1}, x_{i2}, ..., x_{iN}\}
\]

describing product \( i \)'s attributes. A consumer evaluates products sequentially. Let \( \mathbf{x}_t \) be the product that the consumer evaluates at time \( t \), that is, the \( t^{th} \) product to be evaluated. (We do not require each time step to be of the same duration.)

The consumer’s preferences are summarized by preference weights associated with a level of an attribute, also called attribute “partworths”. Let \( w_n \) be the preference weight for attribute \( n \), and \( \mathbf{w} = \{w_1, w_2, ..., w_N\} \) be the consumer’s preferences. For directed sequential search without revision of decision criteria, we assume that the consumer knows the \( \mathbf{w} \). If the consumer purchases product \( i \), the consumer gets utility \( U_i \) from product \( i \). The consumer derives utility from purchasing a product as given by the standard additive model:

\[ U_i = \sum_{n=1}^{N} w_n x_{in} \]

In the more general case with more than two levels, \( w_{nlt} \) represents the weight of level \( l \) of attribute \( n \), and \( x_{inl} \) has value 1 if product \( i \) has attribute \( n \) at level \( l \), and 0 otherwise.
Next, we set up the modeling framework for sequential search, in which a consumer evaluates one product at a time with some cost. The fundamental framework for such models was established by Weitzman (1979), who studies search over products, $i$, and assumes that when a consumer evaluates a product, the consumer learns the utility of the product. In our analyses we focus on one-time purchases (initial purchases) of high-value “durable” goods and services such as those in the opening paragraphs of this paper. For such products the consumer is likely to take both search and choice seriously.

Prior to evaluation, the consumer is uncertain about the utility of the product, but has beliefs about the utility of the product as described by a cumulative probability density function, $F_i(U_i)$. Extending this model to search over multi-attribute products without preference discovery, the consumer is uncertain about the attributes of the product, $x_i$. The uncertainty with respect to $x_i$ induces uncertainty with respect to $U_i$ which we write as $F_i(w'x_i)$. The specific functional form of the consumers’ belief about $x_i$ and what it corresponds to is discussed in Section 4.2.

To describe search, we partition the set of available products into those that have already been searched up to time $t$, $S_t$, and those that have not been searched, $S_t^c$. If the consumer terminates and does not purchase a product, the consumer receives a known utility for the outside good, $B$. At any time the consumer can terminate search and receive utility equal to the maximum over all searched products and the outside option, which we denote $U_t^* = \max \{B, \max_{i \in S_t} [w'x_i] \}$. The state of the system at any $t$ is $\{U_t^*, S_t \}$. Let $J(U_t^*, S_t)$ be the value of to the consumer of being in state $\{U_t^*, S_t \}$.

The consumer will continue searching if she can gain more from the search than the cost of search. Let $c_i$ be the cost of evaluating the product $i$. To solve the search problem, the consumer must solve a dynamic program. At each time $t$, the consumer chooses between terminating and collecting $U_t^*$, evaluating another product. If the consumer evaluates product $j$, then in the next period:

\begin{equation}
U_i(x_i, \bar{w}) = \bar{w}'x_i = \sum_{n=1}^{N} w_n x_{in}
\end{equation}

### 3.2. Existing Models of Sequential Search

2 Because we are studying infrequently purchased goods and services, search happens at a significantly faster clock speed than consumption, hence we do not need to use time discount factors during the search process.
Following standard dynamic programming recursion we write the state transition value function as satisfying the following optimality conditions (the Bellman equation):}

\[
U_{t+1}^* = \begin{cases} 
U_t^* & \text{if } U_j > U_t^* \\
U_j & \text{if } U_j > U_t^*. 
\end{cases}
\]

3.3. Optimal Policies

Equation 2 can be used to find a reservation price at which the consumer is just indifferent between evaluating a product and not evaluating a product. The optimal policy is simple (Weitzman 1979, p. 647):

- If a product is evaluated, it should be the product with the highest reservation price.
- Terminate search whenever the maximum sampled utility, \( U_t^* \), exceeds the reservation prices of all unsearched products.

Weitzman shows that the reservation price, \( z_{it} \), for product \( i \) at time \( t \) is given by:

\[
c_t = \int_{U_t^*}^{\infty} (w'x_i - z_{it})dF_t(w'x_i).
\]

3.4. Comments

There are two implicit assumptions in Equation 2 that we adopt. The first assumption is that we focus on infrequently purchased goods, so the consumer can evaluate several products, but only purchase one (or takes the outside good). Here, evaluating might be visiting a potential home, test driving a car at a dealership, or visiting a college. If Equation 2 were used to model frequently purchased goods (e.g. Erdem and Keane 1996), then the consumer may learn more about a product each time the product is sampled. There might also be ongoing random shocks over consumption occasions due to changes in circumstance or changes in marketing variables. In our setting, we assume that once the consumer has evaluated the product once, there is no benefit to a repeat evaluation. The second assumption is that learning about \( x_i \) does not resolve uncertainty about other products’ attributes, \( x_j \) for \( j \neq i \). For example, if a consumer evaluates an apartment in Brooklyn, the consumer learns about that particular apartment’s condition. Equation 2 assumes that the consumer does not update his beliefs about the distribution of the conditions of other apartments in Brooklyn or about the distribution of conditions of other apartments in...
Manhattan. Relaxing the independence assumption is left to future research.

4. Directed Search with Revision of Decision Criteria

We capture preference discovery by allowing (1) the weight placed on certain attributes to change over time and (2) attribute partworths to depend on the products the consumer has evaluated.

4.1. Revision of Decision Criteria

Let \( \vec{v}^t = \{v^t_1, v^t_2, ..., v^t_N\} \) be the consumers’ attribute partworths at time \( t \). To capture preference discovery, we allow these weights to be a function of the products evaluated up to time \( t \):

\[
\vec{v}^t = f(\vec{v}^1, S_t),
\]

where \( \vec{v}^1 \) represents the initial partworths the consumer started with, and \( S_t \) is the set of products evaluated up to time \( t \).

Let \( \vec{w}^{true} \) be the partworths for the consumer if and when the consumer becomes “expert”: if the consumer were to search all \( I \) products, her preference weights will converge to \( \vec{w}^{true} \). For novice consumers, the \( \vec{v}^1 \) likely underweight some attribute levels and overweight other attribute levels relative to \( \vec{w}^{true} \). For expert consumers, \( \vec{v}^1 \equiv \vec{w}^{true} \).

Suppose a consumer, who has heretofore not considered the quality of the maintenance company, visits an apartment and talks to tenants about the maintenance company. The tenants praise the maintenance company and the consumer comes to realize she should place a high weight on the quality of the maintenance company. In this case, the visit caused \( v^t_h = \vec{w}^{true}_{maintenance\,company} \) to change from a small weight (if any) to the final weight, \( \vec{v}^t_{maintenance\,company} \). For simplicity, we make the following functional form assumption for the function in Equation 3:

\[
v^t_h = \begin{cases} 
  v^0_{in} & \text{if } x_{in} = 0 \text{ for all } i \in S_t \\
  \vec{w}^{true}_{in} & \text{if } x_{in} = 1 \text{ for some } i \in S_t
\end{cases}
\]

That is, consumers revise their criteria to accommodate the new attribute after evaluating a product with that attribute, and the weight immediately changes to its final value. Note that this is a model of preference discovery via surprise. The consumer might anticipate that she will learn something by evaluating a product (e.g., visiting an apartment), but the model assumes the consumer cannot anticipate that she will learn about an attribute that was heretofore not
important to the consumer. In the above example, before visiting the apartment, we assume that the consumer did not even consider the quality of the maintenance company as relevant to her choice of apartments.

There are two things that are revealed to the consumer after evaluating a product. The first is the product’s attributes. This is anticipated by the consumer: if attribute \( n \) is important to the consumer, resolving the uncertainty in \( x_{in} \) will resolve the uncertainty in \( U_i \). Of course, an attribute will only play a role in the decision of which product to search if that attribute has high weight.

The second, which the consumer cannot anticipate, is the change in attribute weights, because the consumer has never experienced \( x_{in} = 1 \). In fact, if \( v^t_n = 0 \) for attribute \( n \), then, a priori, attribute \( n \) will not play a role in choosing which product to evaluate. While this model is stylized, it is more general if we recode the \( v^t_n \) to represent changes in partworths rather than partworths per se. Because the consumer cannot anticipate which attributes’ weights will change, the consumer cannot anticipate which product evaluations will change weights. Thus, the a priori gain due to preference discovery does not vary by product.

The consumer might have a general belief that evaluation may expose the consumer to new attributes, but the consumer cannot anticipate the specific \( v^t_n \) that will change. The modeling framework can incorporate this general belief, which depends on \( t \) but not \( i \), as a change in the cost or benefit of evaluating a product. A constant change in \( c_i \) for all \( i \) does not change the model, so we leave to future research the explicit modeling of the general belief about the benefits of searching for preference discovery.

### 4.2. Uncertainty in the Levels of Product Attributes

The values of the levels of a product’s attributes prior to evaluation are characterized by a belief distribution to the consumer. The belief distribution represents the information a customer can obtain at negligible cost without costly evaluation of a product.

Because an attribute is described by finitely many levels, beliefs are modeled with a multinomial distribution with parameters, \( \vec{p}_{in} = \{p_{in1}, p_{in2}, ..., p_{inL_n}\} \) for all levels \( l \) of each attribute \( n \) for product \( i \). Recalling that \( x_{inl} = 0 \) or 1 and that \( \sum_l x_{inl} = 1 \), the probability mass function is:

\[
(5) \quad f_{in}(\vec{x}_{in}) = p_{in1}^{x_{in1}} p_{in2}^{x_{in2}} \cdots p_{inL_n}^{x_{inL_n}}.
\]
As in Equation 2, belief distributions are independent over products. Belief distributions are also independent over attributes, that is, the consumer’s belief about a particular apartment’s air-conditioning system is independent of the consumer’s belief about whether or not the apartment is near a supermarket. While independence is a simplifying assumption we make in this paper, the model can be readily generalized to account for correlations.

4.3. Optimal Search with Preference Discovery

At any point in the search process, the novice consumer searches with his/her preferences at that point in the process, \( v_t \), rather than \( w^{true} \). The revised Bellman equation at time \( t \) is:

\[
J(U^*_t, \bar{S}_t) = \max \left\{ U^*_t, \max_{j \in S_t} \left\{ -c_i + J(U^*_t, (\bar{S}_t - \{j\})) \cdot \int_{-\infty}^{U^*_t} dF_t(\tilde{\nu}^{t^*}X_j) \right\} \right\}
\]

When \( v^t \neq w^{true} \), Equation 6 might imply a different product to evaluate than does Equation 2. The consumer evaluates that product and resolves the uncertainty about \( x^t_i \). Resolving the uncertainty in \( x^t_i \) resolves the uncertainty in \( U^*_t = v^{t^*}x^t_i \). (Recall that \( x^t_i \) is the product, if any, that the consumer chooses to evaluate at \( t \).)

Observing \( x^t_i \) also changes attribute weights: \( v^t \rightarrow v^{t+1} \). In period \( t + 1 \), the consumer searches with the new attribute weights, \( v^{t+1} \), and new maximum utility, \( U^*_{t+1} \). For example, suppose that at time \( t \), the consumer chooses apartments to visit without any consideration of nearby playgrounds, and, by luck, visits an apartment with a playground across the street. If the consumer decides that she would value a playground, then, when she searches in \( t + 1 \), she chooses the next apartment to visit placing a much higher weight on the playground. This two-way relationship between examining products and discovering preferences is shown schematically in Figure 2.

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Figure 2. Schematic of search and discovery when decision criteria can be revised

As the consumer moves through the search process in Figure 2, his decision criteria evolve as he discovers his own preferences, and the new decision criteria, in turn, determine his preferred product to evaluate.

5. Evidence for Revision of Decision Criteria

In this section, we report the results of two studies that provide evidence for revision of decision criteria as a result of preference discovery. The first study relies on qualitative interviews with real estate agents.

The second study is a laboratory study in which we elicit preferences before and after subjects evaluate apartments. The basic structure of the apartment evaluation study is that (1) consumers articulate their preferences for a product category, (2) they search in that product category, and (3) they update their preferences (if appropriate) after search. We expected that some consumers would change their decision criteria (dorm-living novices without apartment hunting experience) and some would not (experts with substantial apartment-hunting experience). To draw both experts and novices, we used subjects from a pool of students attending college in New York City (NYC).

5.1. Study 1: Qualitative Interviews with Realtors

To understand better the communication between a home buyer and real estate agents who help them in their search, we interviewed 12 realtors in a densely-populated residential neighborhood in Boston. The market is quite competitive among realtors—there are at least
fifteen offices with multiple agents along a quarter-mile stretch of a single street in the neighborhood. In this market, realtors are aware of losing clients to other realtors and well-aware of the impact of negative word of mouth. Although we had no way of verifying their stated beliefs, the realtors claimed that the market rewards benevolence, as it is easy for a buyer to switch to working with another agent if their current agent fails to provide good recommendations.

There were three primary insights from the interviews. (1) Realtors are aware that consumers discover their preferences, and as a result revise their decision criteria as they view apartments (condos). (2) Realtors are aware that expert consumers have more stable decision criteria than novice consumers. (3) Realtors take preference discovery into account in choosing which apartments to recommend. For example, the following quotes are typical of those we obtained from realtors.

- “Often what people start out thinking they want is not what they end up wanting.”
- “Let’s say they tell you they want three things, like renovated kitchen, pet friendly, and up to $2500. I find them something that has those 3. Then they get there and tell me they hate the view and won’t take it because of that.”
- “People may not think about what common areas look like, but once they actually go out and see it, they realize that they will be affected by it.”
- “Let’s say someone is looking for a 1 bedroom with a good layout. I show them one, and then I walk in the bedroom and open up a French door to a private deck. They love that, and want me to look for more apartments with a deck.”
- “It does happen, not very often, that they see just one [apartment] and take it. Usually with people who have been living (in this neighborhood) for a long time and know the area and know exactly what they want.”

5.2. Study 2: Preference Elicitation to Measure Changes in Decision Criteria

The purpose of the study is twofold: (a) providing empirical validation to our modeling assumptions and (b) measuring the parameters of the model.

To apply the proposed model to an applied setting, such as recommending houses to new home buyers, one would first need to train the parameters $V^0$ and $W^{true}$. Traditionally, search models have relied on secondary data, such as transactions, to infer customer preferences (e.g. Erdem and Keane 1996, Seiler 2013). However, our model requires more fine-grained search
data, in order to reliably estimate the evolution of decision criteria during search. Purchase data alone are not sufficient, particularly given that the interesting practical applications for which our model is relevant correspond to infrequently purchased items. For these reasons, we propose a method to measure the evolution of decision criteria using preference elicitation methods, which will allow us to get at the decision criteria directly.

Broadly, the study involves participants stating their decision criteria for renting an apartment, and, after evaluating several example apartments, being given a chance to revise their decision criteria. We find that 53% of the participants opt-in to write a revision after the apartment evaluation task.

To the best of our knowledge, this is the first study to measure preferences over time and track how they evolve. Measuring the evolution of decision criteria in a lab environment is challenging for two main reasons:

(1) **External validity.** Primary data methods raise concerns about external validity of the obtained parameters – it is unclear whether preferences stated in the laboratory environment would translate to real-life choices. To help improve the external validity of our measurements, we make the task as realistic as possible to a real apartment search process, and use incentive alignment (described in the next section).

(2) **Effects of Measurement.** The construct we want to measure is how decision criteria evolve in response to evaluating products. However, most preference elicitation tools, such as conjoint analysis, measure preferences by having consumers evaluate products. If our hypothesis is true, and evaluating products does cause consumers to revise their decision criteria, then completing a conjoint task would already induce the change. Even self-explicated methods are intrusive because the task typically lists the relevant attributes and asks the respondent to rate or rank them (see Green and Srinivasan 1990). We propose using an unstructured direct elicitation method which is less intrusive.

### 5.2.1 Incentive Alignment for Study 2

A key challenge in identifying revision of decision criteria is to give subjects sufficient incentives to report their decision criteria accurately. To address this challenge, we sought to make both preference elicitation, before and after product evaluation, incentive aligned. A task is incentive aligned, rather than the more-formal incentive compatible, if: “subjects believe (1) it is in their best interests to think hard and tell the truth; (2) it is, as much as feasible, in their best
interests to do so; and (3) there is no way, that is obvious to the subjects, they can improve their welfare by ‘cheating’” (Ding, et al. 2005, p. 120). We adopt the incentive alignment procedure and the preference elicitation task from Ding, et al. (2011). In particular, subjects were told that one subject from a small sample would be selected and given a reasonable chance at receiving free rent for one year (up to $20,000). The chosen subject would receive $100 for sure and get to draw two envelopes out of twenty. If both contained winning cards, the subject received the free rent.³

If the subject received free rent, an apartment would be chosen for them by two independent judges using the preferences that the subject articulated in the study. To avoid elicited preferences that were too specific, the judges would choose from a secret set and the judges’ decisions would be audited. If the two judges did not agree, a third judge would be used. If the apartment’s rent was less than $20,000, the subject would receive the rest in cash. (In the actual study, the winning student did not draw two winning envelopes, but had she done so, the $20,000 would have been paid by prize indemnity insurance.)

Both pretests and post-tests suggested that the subjects understood the incentives, took the tasks seriously, and invested substantial effort in both the initial preference elicitation and updates to preference elicitation. If the incentives had not been sufficient, subjects might have shirked on effort for preference elicitation or search. If they shirked on preference elicitation (reporting incomplete preferences), they would almost surely have shirked on the optional preference revision task. If they shirked on search, they would be less likely to discover preferences. Both types of shirking likely bias the study against finding revision of decision criteria.

5.2.2. Preference Elicitation Task

We chose a preference elicitation task that was flexible, required low subject effort, did not itself induce preference discovery, was compatible with incentive alignment, and had proven accurate for eliciting preference for the attributes of durable products. The task was unstructured direct elicitation as described in Ding, et al. (2011).

Subjects were instructed to: “Provide instructions to Dan and Emily who have been hired to select an apartment for you if you win the lottery. They do not know anything about this study,

³ The chances of drawing two winning cards are 1 in 190. However, subjects perceive the chances as much higher as indicated by the excitement and overwhelming interest in response to a request for subjects from the university’s subject pool.
and will only read your instructions.” Subjects were given suggestions about their instructions, such as “State as many instructions as possible, so that the agents have the best information of your preferences”. When they were done, they clicked “Submit my email.”

5.2.3. Evaluate Example Apartments

After stating initial preferences, subjects evaluated twelve apartment listings. The listings were chosen from actual listings in NYC and each included verbal descriptions and images and varied. The listings varied on attribute levels that had been identified in pretests and by browsing local listings. Figure 7 is one example. The listings spanned the set of available attributes and were the type of apartments normally chosen by students at the university.

It was not feasible for subjects to visit the apartments. Instead, we induced careful evaluation as a surrogate for search. Subjects rated each listing and provided “one or two reasons for [his/her] rating.” Pretests indicated that this task induced subjects to evaluate each listing carefully. This surrogate is likely to underestimate preference discovery relative to the evaluation of real apartments.

5.2.4. Optional Preference Updating Task

One danger with re-measuring preferences is that participants might perceive that the experimenter wants the participant to revise her preferences. The preference revision task was designed and pretested carefully to minimize such demand artifacts. Participants were shown their original letter and were asked “Is there anything about your response that could be improved to help the agent make a better decision on your behalf?” Participants could select “YES, I would like to update these instructions to better reflect my preferences,” or “NO, these instructions are accurate and complete.” If participants chose to revise, they could submit their revision as additional information, in which case the judge would see both the original and new email. There was no additional reward for completing this task, other than the implicit reward that providing better instructions would help “Dan and Emily” make better choices on the participant’s behalf. Participants could skip this task if they felt their initial stated preferences still described their preferences. Participants were not told about this task when they stated their initial preferences, so they could not anticipate that revisions were possible.
Williamsburg, Brooklyn

Bedrooms: 2
Price $1,850

Very large living area
Luxurious & very spacious kitchen with stainless steel appliances, trenched cabinetry and countertop space
2 Nice size bedrooms with big windows.
Closest space
Washer/dryer Hook-up in unit

Nearby subway stations:
- Chauncey St (0.18 mi) - J train (1 transfer to get to NYU)
- Bushwick Av - Aberdeen St (0.19 mi) - L train (1 transfer to NYU)

![Image of apartment kitchen]

On the following scale, how well does this apartment fit your needs?

Very Poor | Poor | Fair | Good | Very Good

Please provide one or two reasons for your rating

![Rating scale]

Figure 3. Example Apartment Listing
Screen shot from survey, edited to fit on one page. The actual listing in the survey included five images.

5.2.5. Results: Participants Revised Their Decision Criteria
Of the 79 study participants, 42 revised their decision criteria substantially. (An additional 6 subjects provided clarifications.) Responses varied in length with an average of 231 words and a standard deviation of 160 words.

As befits the product category, real estate, location was the most-revised attribute. For example, the following respondent expanded the set of locations that he was willing to consider. Prior to evaluating the listings, he would have limited his search to apartments within walking distance of the university. After search he expanded his search, in part, because he discovered that apartments that were further away had attributes he had come to desire. These attributes were not weighed nearly as heavily prior to preference discovery.

**Prior to evaluation of listings.** “Areas that I am interested in are West and East Village, St. Marks, 14th St., Soho, Chinatown, or any other areas within a 15min walking distance from NYU. I would also consider any apartments available uptown that are close to trains.”

**After evaluation of listing.** Areas that I am interested in are West and East Village, St. Marks, 14th St., Soho, Chinatown, or any other areas within a 15min walking distance from NYU. I would also consider any apartments available uptown that are close to trains. Additionally, I would extend my location preferences around the city preferably only NYC and not NJ if there are places in great neighborhoods with a great price and large room. I would actually prefer Brooklyn or Queens if there is a larger place and better neighborhood than Manhattan.”

But changes in the location criterion may simply be evidence of customers learning more about the prices in the NYC housing market, rather than discovering their own preferences. However, participants revised eighteen other attributes as indicated in Figure 9. Below are example phrases that participants added to their revisions:

“I prefer to have clean and new kitchen and the room can be smaller.”

“Central AC would add greatly to my valuation of the apartment.”

“I’d prefer an apartment with some exposed brick furnishings, a loft-like setup, a gym, recently renovated, rent-controlled, thick/relatively soundproof walls, and/or in a prewar building but those are not deciding factors.”

“[The preferred apartment would] have heater/AC; hardwood floors are preferable over carpet; have ample sunlight; not located on main roads (e.g. Broadway)”
Figure 4. Attribute Preferences that Were Revised Most Often by Participants

In summary, the incentive-aligned study suggests that consumers revise preferences substantially as the result of a realistic evaluation of apartments in NYC. In this study, the experimenter “recommended” twelve apartments to evaluate. Had participants not evaluated these recommendations, they would have used their initial stated preferences and, likely, they would not have searched as broadly. With the recommendations, participants used their revised preferences and, likely, their (in vivo) search process would have changed.

5.3. Comments

The incentive-aligned study likely underestimates revision of decision criteria because participants evaluate listings rather than real apartments. Furthermore, any unobserved shirking is likely to underestimate the resulting revision of decision criteria. Nonetheless, while preference discovery is one interpretation of the data, there are alternative explanations.

The model proposed in §3 is stylized in order to isolate revision of decision criteria. This paper addresses one important mechanism for revision of decision criteria —preference discovery due to product evaluation during search. However, there are other ways in which
consumers might discover their preferences. For example, many websites recommend to consumers which attributes to consider when evaluating products such as electronics, used cars, dietary supplements, etc. In reality, consumers are likely to seek such information help to form \( V^1 \). In some cases consumers will find that \( V^1 = W^{true} \), but in other cases consumers will experience additional self-discovery as they evaluate products. Even if a trusted source lists important attributes, “learning by doing” or “learning by evaluation” may still be necessary.

Revision of decision criteria is loosely related to the literature in marketing on consideration sets. In that literature consumers use a consider-then choose rule or a cognitively-simple heuristic such as a lexicographic rule (Hauser and Wernerfelt 1990; Jedidi and Kohli 2005) to determine a choice set. Preference discovery can be extended to include decision heuristics. For example, the consumer might discover or reorder attributes in a lexicographic decision process for consideration and discover preference weights for decisions within the consideration set.

6. Noisy Information and Preference Discovery

The optimal policy for sequential search with constant decision criteria was to evaluate the product with the highest reservation price. Although the computation of the reservation price (Equation 2) depends upon the noise in the consumer’s beliefs about the product attributes, there was no interaction between the optimal policy and noise, other than the decision to stop searching. When we allow decision criteria to change, noise in the consumer’s knowledge of product attributes interacts with preference discovery.

6.1. Analytical Results (Existence) on the Interaction of Noise and Preference Discovery

To motivate the interaction between noise and preference discovery, consider a simple market of two products with two binary attributes. Product 1 has attribute 1 but not attribute 2, and product 2 has attribute 2 but not attribute 1. Without loss of generality, assume \( w^{true}_{21} > w^{true}_{11}, w^{true}_{22} = w^{true}_{12} = 0, \) and \( B = 0 \). An appendix establishes that, for this market:

Proposition 1. If an (expert) consumer knows his/her preferences \( (V^e = W^{true}) \), then the expert consumer finds the best product with minimal search cost when there is no uncertainty in product attributes \((p_{111} = p_{122} = p_{212} = p_{221} = 1)\).

Proposition 2. If a (novice) consumer has not yet discovered his/her preferences \( (V^e \neq W^{true}) \), then the novice consumer may be better off (utility net of search cost) with noisy prior beliefs, that is, when \( p_{111}, p_{122}, p_{212}, p_{221} < 1 \).
The intuition is simple. If the novice consumer under- or over-values some attribute levels and if there is no noise in the attribute levels, then the novice consumer will act on the incorrect preference weights. With incorrect weights the novice consumer will evaluate the product with the lower true utility and will never evaluate the product with higher true utility. The novice consumer will not know what he or she has missed. For example, the consumer might never visit an apartment with a high quality maintenance company. On the other hand, if there is noise in the attribute levels, there are reasonable conditions where the novice consumer will evaluate the better product, update his/her preference weights, and choose the higher utility product.

Proposition 2 is a new phenomenon that is not possible with optimal search alone. Whether the novice consumer is actually better off depends upon the specific values of the $\tilde{p}_{in}$'s and the $V^e$'s. Proposition 2 is an existence proof based on a simple market. The proof extends readily to more products, more attributes, and more levels. However, extending the result analytically to more complicated scenarios is difficult. Instead, we turn to synthetic data to handle the complexity and illustrate that the phenomenon is more general than a $2 \times 2$ market. The synthetic data then allow us to investigate other interesting phenomena.

6.2. Insights Using Synthetic Data: Noise and Preference Discovery

Synthetic data can be used with any number of attributes, attribute levels, and products. We simulate a product space with four attributes at four levels each. If there were no further restrictions on the product space, there would be $4 \times 4 \times 4 \times 4 \times 4 = 1024$ products. To examine whether the results of §4.1 generalize, we allow the market to vary on noise and expertise. To make the markets more realistic, we use a partial factorial design to simulate market efficiency.

6.2.1. Varying noise. Figure 5 illustrates how noise might vary among markets. The market on the left is relatively noisy. Prior to evaluating the product, the consumer believes that each of the four levels of the apartment’s condition are roughly equally likely. Contrast this noise level with that in the market on the right. In that market, the consumer is fairly certain that the apartment has a renovated kitchen.
Figure 5. Varying Levels of Noise in the Consumer’s Prior Beliefs

Each graph plots the $p_{inl}$’s for the four levels ($l = 1$ to 4) of the “condition” attribute, $n$, for product $i$.

To model noise, we draw the $\vec{p}_{in}$ from a Dirichlet distribution. The Dirichlet distribution assures that the $p_{inl}$’s are bounded between 0 and 1 and sum to 1.0 over $l$. Specifically,

$$f(\vec{p}_{in}) = \frac{\Gamma(\sum_{i=1}^{l} a_{in})}{\prod_{i=1}^{l} \Gamma(a_{in})} p_{in1}^{a_{in1}-1} p_{in2}^{a_{in2}-1} \ldots p_{inl}^{a_{inl}-1}$$

where the parameters, $a_{inl}$’s, of the Dirichlet distribution control the noise and $\Gamma(\cdot)$ is the gamma function. This distribution is often used in marketing to model consumer brand choice (e.g. Fader 1993), but here, we use it to model consumer beliefs about discrete attribute values. The parameters control the noise because, with the Dirichlet distribution, $E[p_{inl}] = a_{inl} / \sum_{k=1}^{l} a_{ink}$. For example, the left graph of Figure 5 (high noise) corresponds to $a_{inl} = 1$ for all $l$ for a given apartment $i$ and attribute $n$ (“condition”). The right graph of Figure 5 (low noise) corresponds to $a_{in3} \gg a_{in1}, a_{in2}, a_{in4}$.

In the highest noise situation we set $a_{inl} = 1$ for all $l$. Noise in the consumer’s prior beliefs decreases as $a_{inl}$ increases for the true attribute level. Let $a_{noise}$ control the noise and set $a_{inl} = a_{noise}$ if $x_{inl} = 1$. Otherwise, keep $a_{inl} = 1$. In the synthetic data $a_{noise}$ varies on a logarithmic scale from 1 to 150. Specifically, $a_{noise} = 1, 3.5, 12.2, 42.3,$ and $150$.

6.2.2. Varying Expertise. An expert consumer starts at $t = 1$ with $V^t \cong W^{true}$; a novice consumer starts at $t = 1$ with a $V^1$ that can be very different from $W^{true}$. Our goal is to model consumer expertise, as well as allow for heterogeneity among customers.

It is standard to model consumer heterogeneity by modeling partworths as draws from a normal

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4 For this specific plot, values $a_{in1} = a_{in2} = a_{in4} = 1$ were used for both plots, and $a_{in3} = 1$ for the left plot and $a_{in3} = 50$ for the right plot.
distribution (e.g. Allenby and Rossi 1998). To capture consumer expertise, we draw the initial preference weights, $v_{nl}^1$, and the true weights, $w_{nl}^{true}$ from a joint normal distribution for each of 500 consumers for each synthetic data run. Preference weights can be positive or negative—a consumer may prefer or not prefer to have an apartment with exposed brick, thus, we use a zero-mean distribution with unit variances. (The results are not sensitive to these restrictions.) A correlation parameter, $\rho$, captures expertise. Highly correlated $v_{nl}^1$ and $w_{nl}^{true}$ correspond to high expertise and uncorrelated $v_{nl}^1$ and $w_{nl}^{true}$ correspond to low expertise. Specifically,

$$
\begin{pmatrix}
W_{nl} \\
v_{nl}^1
\end{pmatrix} \sim \mathcal{N}
\begin{pmatrix}
0 \\
0
\end{pmatrix},
\begin{pmatrix}
1 & \rho \\
\rho & 1
\end{pmatrix}
$$

6.2.3. Simulating market efficiency. A market with all 1024 products is not particularly efficient because, for a given set of preference weights, $W^{true}$, there exist dominated products. It is more realistic to allow some attribute levels to be anti-correlated (e.g., homes in a certain neighborhood are old, cars with large engines have low fuel efficiency, Porsche does not make pickup trucks, nannies with daycare experience refuse to do housework). In low market efficiency, all 1024 products would be available. In a more efficient market, some products are deleted based on a symmetric 20 x 20 anti-correlation matrix, $C$, with elements, $c_{kj}$. The rows and the columns correspond to attribute levels (5 attributes at 4 levels each). The probability that product $i$ is deleted is the multiplication of the $c_{jk}$ for all pairs of attribute levels in product $i$ for which $x_{int} = 1$. For each synthetic-data run, we draw $c_{kj} \sim \text{Beta}(0.1,0.8)$. Results are not sensitive to the choice of parameters. Including these unlikely feature combinations in simulating the market ensures that the consumer will have to make some tradeoffs, and therefore benefits from knowing more than just the level with the highest partworth for each attribute.

6.3. Search Costs and Net Rewards for Novice and Expert Consumers

We begin with expert consumers setting $\rho = 1$ such that $v_{nl}^1 = w_{nl}^{true}$, and search with preference discovery (Equation 6) reduces to the special case of search without preference discovery (Equation 1). Figure 3 plots the average search time and average net payoff for expert consumers when they search optimally. The results are as expected. When there is little noise and consumers know their preferences, they find the best product quickly and earn high net payoffs (utility net of search costs). However, as noise increases, it is more difficult for the consumers to find the best product. They search longer and do not earn payoffs that are as high.
Because the chosen values of $\alpha_{\text{noise}}$ are somewhat arbitrary, the important insight from Figure 3 is that search costs increase monotonically as noise increases and that net payoffs decrease monotonically as noise increases.

Analyses provide an interesting contrast when novice consumers discover their preferences (setting $\rho = 0$). Search time increases with noise, but the net payoff is no longer monotonic in noise. Then net payoff increases over the first four levels of noise before decreasing at extremely high noise. When $\rho = 0.7$, the results are between those of Figures 3 and 4. For another perspective on the interaction of noise and expertise, we compare the net rewards obtained by novice consumers ($\rho = 0$) when noise is high ($\alpha_{\text{noise}} = 1$) versus when noise is low ($\alpha_{\text{noise}} = 150$). Roughly 60% of the consumers (299 out of 500) obtain higher rewards when noise is high. These results are consistent with the analytic results and suggest that when consumers can revise their decision criteria as they discover preferences through search, noise in prior beliefs can increase net payoffs.
7. Product Recommendations and Revision of Decision Criteria

§3 and §4 ignored external recommendation, but agents are sometimes involved in the search for high-value products and services. Consumer-centric recommendation systems are common on the Internet. Websites such as Netflix, Youtube, SiriusXM radio, Kelly Blue Book, and other platforms such as Xbox game console provide recommendations to consumers. Many of these firms seek to build trust by recommending the products that they believe are in the best interests of the consumer. There has been substantial research in developing recommender systems to aid consumers. Typically, these systems seek to recommend the product that the consumer will prefer (Adomavičius and Tuzhilin (2005), Fong (2014), Ghose, Ipeirotis and Li (2012), Liberali, Urban and Hauser (2013)). Sometimes recommendations come from human agents, such as real estate agents or college counselors. In the presence of preference discovery, the product recommendation has the power to change what the consumer will look for after examining the recommended product, a recommendation has much more influence than simply bringing the recommended product to the consumer’s attention. In fact, we find that recommendations that ultimately lead to good purchase decisions that are optimal for the consumer need not themselves be high utility products. Rather, they expose consumers to new, previously undervalued attributes, thus making the consumer more efficient in his future search.

In this paper, we limit the discussion to benevolent agents, and abstract away from misaligned incentives in which an agent may try to push the consumer to purchase an alternative that is not optimal for the consumer. While sometimes the agent’s incentives may not be aligned with the consumer’s, such agents can also be benevolent if the market is highly competitive and/or if the agent wishes to act to gain the consumer’s trust to benefit a long-term relationship (Morgan and Hunt 1984). For example, Best Buy does not pay commission and instructs their salespeople to help consumers find the best product, and Netflix is simply interested in helping their customers find many good films, such that the consumers continue renewing their subscriptions. We begin by examining how preference discovery interacts with benevolent recommendations. We then discuss how preference discovery enables non-benevolent recommendations to game the system, but do not model the full game.

7.1. The Effect of an Initial Recommendation

To simulate recommendations, we use the same synthetic data regime, but modify the search process. We allow the recommender (agent or virtual agent) to recommend one product at
$t = 1$. The consumer evaluates that product and then proceeds with optimal search using Equation 6. Throughout the process (novice) consumers discover preferences.

We plot the results of optimal search separately for every possible recommendation. The consumer often will not choose the recommended product and the recommendation often influences the consumer’s future search path. For example, the benevolent agent might recommend a product with true utility of $W^{true}X_r = 3.9$, but, after search, the consumer might purchase a product with true utility of $W^{true}X_i = 7.5$.

Figure 5 plots the results for an illustrative consumer. Each point in Figure 5 represents an initial recommendation. The horizontal axis is the utility of the recommended product and the vertical axis is the net payoff (utility net of search costs) that the consumer earns from the product that is chosen after optimal search. In Figure 5 the final choice has an equal or higher payoff than any recommended product. (In general, the final choice might not always be higher because there are search costs and because $V^t$ might not equal $W^{true}$ when search terminates.) The highest utility product is indicated with a solid arrow (“Type A”).
Even with preference discovery, it is a good strategy to recommend the highest utility product for this consumer. That recommendation gives close to the highest net reward. However, Figure 8 illustrates other phenomena. For example, a low-utility initial recommendation ("Type B"), as indicated by the dotted arrow, also yields a high reward. That recommendation does well because it helps the consumer to discover his/her preferences. An example would be a realtor showing his client an unacceptable apartment but in a neighborhood that the consumer likes but did not previously know about. That low-utility recommendation actually yields a higher net reward than a recommendation with substantially higher utility ("Type C", shown with a dashed arrow on the graph).
The higher-utility recommendation (Type C) does not encourage as much preference discovery as the lower-utility recommendation (Type B). These phenomena are not specific to the illustrative consumer in Figure 8. Figure 9 repeats the plots for fifteen randomly-chosen consumers. Note that not all consumers are impacted by recommendations: some consumers are able to find the best product without any recommendation, and no matter what they are recommended at time 1, they end up with the best product. We obtain similar insights from all 500 consumers.

7.2. Constrained Recommendations

Suppose that the recommendation system (or agent) were constrained in its ability to recommend products. For example, a realtor might judge that an apartment shopper is not serious and may want to limit recommendations to open houses. Alternatively, a recommender’s database may be limited to a subset of the products on the market.

To illustrate this scenario, suppose that the recommender could only choose between the two products indicated by dotted- and dashed- arrows in Figure 8. In this case, the benevolent agent would recommend the lower-utility product under the understanding that it would help the consumer discover his/her preferences. This contradicts the design of almost all extant virtual recommender systems.

This illustration suggests that recommendation systems that explicitly model preference discovery might serve consumers better. Such research might also address the question as to how the recommendation system might anticipate $W$ and learn $V^1$. It is beyond the scope of this paper to develop such recommendation systems. As a first step, §3 suggests that preference discovery might be observed and measured, although the methods of §3 would need to be developed further if a virtual recommendation system were to anticipate preference discovery.
Figure 9. Results of Initial Recommendations for Twenty-Four Consumers
7.3. Precision of Recommendation Systems

In the traditional setting without consumer preference discovery, a key challenge for a recommendation system is to correctly predict how much a user will like certain items, and then choose the highest utility item. In the proposed modeling framework, a more important challenge is to identify on which product attributes the discrepancy between initial and true preferences is likely to occur, and expose the consumer to products with those attributes.

7.4. Agents that are Not Benevolent

While the full game theoretic model of the interaction between a buyer and an agent is beyond the scope of this paper, we provide some insights of how revision of decision criteria on the part of the consumer may play out in such an interaction. Suppose that an agent was not benevolent. That agent might be rewarded more highly if the consumer chooses from a subset of the available products. For example, some realtors get a higher reward if they are the listing agent, or an online retailer might have higher margins on some products than others (e.g. Ghose, Ipeirotis and Li (2013), Librali, Donkers, and Stremersch (2014)). However, the non-benevolent agent may not wish to make it explicit to the consumer that the agent is limiting search to a subset of products.

Figures 8 and 9 illustrate nicely that initial recommendations matter. The agent can use those recommendations to steer the consumer while seeming benevolent. For example, by recommending the “Type C” product in Figure 8, the agent can recommend a product with high initial utility (although not the highest). As the consumer searches and discovers his/her preferences, the consumer ends up buying the recommended product. The consumer feels good about the search because the consumer had control of the search after the initial recommendation. The consumer never realizes that he might have found a higher-utility product, because he never updated his decision rule to incorporate his preferences for attributes with low $v_{nl}^f$ but high $w_{nl}^{true}$. By recommending an initial product, the agent steered the consumer to a profitable product and the consumer is satisfied.

The analysis of non-benevolent agents is within the realm of game theory and is an exciting area to investigate with revised decision criteria. The exact results will depend upon the specifics of the game such as the product set, the initial preferences, the true preferences, the profits assigned to each consumer choice, the consumer’s beliefs about the agent’s incentives, and the consumer’s knowledge.
8. Conclusions and Potential Future Directions

This paper demonstrates how consumers’ decision criteria change during the course of search. The key idea is that when evaluating products, consumers experience attribute levels that hitherto had not been considered and may revise their decision rule to account for these attributes. Analytically, preference discovery changes the optimization objective function to use parameters \( V^t \) rather than \( W^{true} \). The focus is on high-involvement infrequently purchased products. The key contributions of the paper include (1) a modeling framework for the evolution of decision criteria through preference discovery, (2) validation of the model assumptions using sequential direct preference elicitation, and (3) derivation of insights and implications for product recommendations.

The phenomenon of attribute weights changing in response to evaluating products is relevant for firms’ strategic decisions other than product recommendations. For example, Dzyabura and Jagabathula (2014) demonstrate implications for retail assortments in a brick and mortar store when consumers can visit the store to evaluate products and then purchase, possibly a different product, through the online channel. In design engineering, She and Macdonald (2013) demonstrate how evaluating toasters with certain “trigger” features increases the weight consumers place on sustainability.

Our work lays the foundation for several interesting future research directions, some of which we discuss below.

Agent Incentives. Our primary focus is on benevolent recommending agents, whose goal it is to help the consumer find the best product (e.g. Pu et al. 2011). We also demonstrate how a non-benevolent agent can lead the consumer to buy a product that is suboptimal for the consumer. However, a full game-theoretic model of a sales-agent’s interaction with a consumer who may revise his decision criteria in response to evaluating certain products would be necessary to understand the outcomes if incentives are not aligned: the agent would then be able to strategically recommend products to guide the consumer towards a purchase decision that is more profitable for the agent.

Machine Learning Tools to Detect Shifts in Decision Criteria. We propose a method to measure shifts in decision criteria using primary data. However, in order to implement an online system that is able to account for preference discovery, algorithms are required to detect which features consumers tend to over- and under-estimate. Qualitative evidence suggests that experienced
human agents (see interviews with realtors and childcare agency) have learned these attributes by observing their clients’ behavior over time. Machine learning algorithms can be developed to learn them from users’ browsing behavior.

*Models of Evolution of Decision Criteria.* In this paper, we assume a particular model of how the decision criteria evolve. This model can be extended to allow for more sophisticated revision rules. For example, a single attribute may remind the consumer of other, related attributes. If a consumer is only considering purchasing a sedan and happens to test drive a hatchback and like it, he may also begin to consider small SUVs.

*Anticipation of Preference Discovery.* A novice consumer may suspect that he may have failed to consider some relevant attributes in his decision criteria, and strategically search more products to make sure he is not missing something. This is different than having uncertainty over attribute weights. Rather, the consumer would have a belief distribution over the number of possibly missed attributes, and update this distribution when he evaluates a product and does/does not discover a new attribute. After seeing several products in a row and not discovering any new attributes, the consumer should become convinced that he has now recalled all relevant attributes. To the best of our knowledge, such beliefs about the existence of unknown unknowns has not been modeled in consumer decision theory and may have interesting implications.
References


Appendix: Proofs

Proposition 1: A consumer who knows his preferences from the start, i.e. $v^1 = w$, is best off when he also knows the product attributes without any uncertainty, i.e. $p_1 = 1$ and $p_2 = 0$.

Proof:

At time $t = 1$, the equations for the reservation prices are:

\[ c = p_1 \cdot (v^1_1 - z_{11}) + (1 - p_1) \cdot (v^1_2 - z_{11}) = p_1 \cdot v^1_1 + (1 - p_1) \cdot v^1_2 - z_{11}, \text{ and} \]
\[ c = p_2 \cdot (v^1_1 - z_{21}) + (1 - p_2) \cdot (v^1_2 - z_{21}) = p_2 \cdot v^1_1 + (1 - p_2) \cdot v^1_2 - z_{21} \]

The highest possible payoff is $\max\{0, w_2 - c\}$. If $w_2 - c > 0$, the highest payoff corresponds to searching one time and purchasing product 2; otherwise, the highest payoff corresponds to not searching and taking the outside good.

Suppose the consumer knows his preferences from the start, so that $v^1 = w$. Then the reservation prices are:

\[ z_{11} = p_1 \cdot w_1 + (1 - p_1) \cdot w_2 - c \]
\[ z_{21} = p_2 \cdot w_1 + (1 - p_2) \cdot w_2 - c \]

If $p_1 = 1$ and $p_2 = 0$, then $z_{11} = w_1 - c$ and $z_{21} = w_2 - c$.

Since $w_2 > w_1$, the highest reservation price is that of product 2 (which is the correct “best” product). If $z_{21} - c < 0$, the consumer does not evaluate this product, stops searching, and takes the outside good. His payoff is 0, which is the maximum possible in this case. If $z_{21} - c > 0$, the consumer evaluates this product. Since the beliefs were already certain, and the weights were correct, they remain unchanged. In the next time period, $U^{2*} = w_2$ and the reservation price of the remaining product is $z_{12} = w_1 - c < U^{2*}$, so he does not search any longer, and purchases product 2. His net payoff is $w_2 - c$, which is the maximum possible in this case.
**Proposition 2**: If $v^1 \neq w$, the consumer may be better off with noisy information about product attributes, i.e. $p_1 < 1$ and/or $p_2 > 0$, than with perfect knowledge of product attributes without uncertainty.

**Proof**: Suppose that the consumer is correct about the weight of the first attribute level, $v^1_1 = w_1$, but undervalues the second attribute, $v^1_2 < w_2$. Suppose further that $0 < v^1_2 < v^1_1 < w_2$. The highest possible payoff is $w_2 - c$

Case 1: $p_1 = 1$ and $p_2 = 0$.

The reservation prices are

$$z_{11} = v^1_1 - c = w_1 - c$$

$$z_{21} = v^1_2 - c$$

Since $v^1_2 < v^1_1$, then $z_{11} > z_{21}$, and the consumer searches the first product at time 1, and at time 2 we have $U^{2*} = w_1$ and the reservation price for product 2 is:

$$z_{22} = v^1_2 - c < U^{2*}$$

The consumer terminates the search, purchases product 1, and receives a payoff of $w_1 - c$.

Case 2: $p_1 < 1$ and/or $p_2 > 0$

The reservation prices are:

$$z_{11} = p_1 \cdot w_1 + (1 - p_1) \cdot w_2 - c$$

$$z_{21} = p_2 \cdot w_1 + (1 - p_2) \cdot w_2 - c$$

If $p_2 > p_1$, then $z_{21} > z_{11}$, and consumer searches product 2, and $U^{2*} = w_2$. At time 2 the reservation price of product 1 is

$$z_{12} = p_1 \cdot w_1 + (1 - p_1) \cdot w_2 - c < w_2$$

Since $z_{12} < U^{2*}$, the consumer terminates search and purchases product 2. His net payoff is $w_2 - c$, which is greater than $w_1 - c$ which was the payoff in Case 1.