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Abstract

The advent of electronic environments is bound to have profound effects on consumer decision making. While the exact nature of these influences is only partially known it is clear that consumers could benefit from properly designed electronic agents that know individual users' preferences and can act on their behalf. An examination of the various roles agents perform is presented as a framework for thinking about the design of electronic agents. In addition, a set of goals is established that include both outcome-based measures, such as improving decision quality, as well as process measures like increasing satisfaction and developing trust.

Key words: agents, e-commerce, consumer choice

Introduction

The world of commerce is changing. Due to the pervasive adoption of information technology, we are witnessing the evolution of a new marketplace. Unlike traditional face-

to-face retail settings where a good can be touched, seen, and even tasted, transactions are occurring in computer media environments which do not offer the opportunity for directly experiencing a product. This paper focuses on two aspects of these new environments: the first is the design of such environments themselves. We ask how these environments will affect customer decision making. Our second focus is on how to help consumers make better decisions in these new environments. Here we focus on the concept of an electronic agent, and consider the roles they can play in computer-mediated environments.

Our interest in electronic consumer environments is motivated by two observations. First, in many ways these environments are importantly different from normal ways of conducting commerce. Transactions can occur more quickly and across greater distances than with traditional retailers. Digital goods, such as a digitized recorded performance, or a computer program can be discovered, tested, evaluated, purchased, and delivered all in a few minutes time, and these transactions can easily occur across borders. These environments can also change very quickly and inexpensively. While it is impossible for physical stores to differentially arrange their shelves for each consumer, detailed customization is intimately possible in electronic markets. Finally, these environments can collect and use abundant data about individual customers. In principle, and to some extent in practice, electronic environments allow us to not only observe what is purchased, but also what information is examined on the way to purchase.

However, one observation is unmistakable: despite the increase in computing speed touted by Moore's law, a particular CPU has not changed its capacity: that of the human decision maker. Ultimately, although this decision maker may be faced with more information, a wider variety alternatives, and other benefits, the processing of this information occurs using the same limited information processing capacity as in physical shopping environments. This constraint, unaffected by new technologies, raises an obvious question of; how these new environments affect consumer decisions.

To examine these questions, we look at two aspects of these new decision environments. First we ask how the environment itself may affect consumers decisions, and then we look at the prospects of electronic agents aiding these decision makers.

How Do Electronic Environments Affect Decision Makers?

A casual examination of the popular press suggests that the rise of electronic commerce will be accompanied by an increase of consumer sovereignty. Because the cost of search is reduced, consumers should be empowered and able to search for better products at lower prices (Bakos, 1997). The emerging view is one in which many marketplace imperfections disappear and one in which consumers are in a more powerful position compared with retailers. Alba et al. (1998; Lynch and Ariely, 1998) suggest that this fear is a major reason why many retailers are hesitant to move to the arena of electronic shopping.

However, we think the story may be a bit more complicated. Consumer choice, whether in a physical or electronic environment seems increasingly to be jointly determined by both a consumer's preferences and the features of the task environment. More recent behavioral views suggest several ways in which the choice environment might affect what a consumer

chooses. These views are particularly relevant to electronic environments because the design of these environments is so easy to change. In the next section we review some of this literature.

Preference Construction and Discovery

Many traditional models of consumer choice assume that a consumer's tastes are well articulated, and much like psychophysical functions. A more recent, evolving view suggests that for some kinds of preferences, consumers are constructing guesses about what they prefer (Bettman, Luce, Payne, 1998; Payne, Bettman, and Johnson, 1993; Fischhoff, 1991). Not only are such statements of preferences often constructed on the spot, but they represent at best guesses about what would really maximize hedonic pleasure (Kahneman and Snell, 1990; Lowenstein and Schkade, 1999 review this literature). These guesses are likely to be affected in online environments due to their ability to manipulate the context in which the choice is made.

One example is research by Mandel and Johnson (1998) who show that wallpaper, the background of a web site, can prime the importance of product attributes, and thereby alter choices even with a single brief exposure. Another example comes from Menon and Kahn (1998) who illustrate a possible connection between a users' initial experience with a Web site and subsequent choices, (e.g., a higher level of initial stimulation produces lower tendencies to choose novel products, less responsiveness to promotional incentives, and fewer unplanned purchases). The flexibility of the electronic environment raises both a caution and an opportunity. If electronic retailers can alter environments to bias choices in their favor, social welfare could drop. However, opportunity arises as increased competition among electronic retailers make it less likely that retailers will survive who convince customers to purchase products that are not in their best interest. The relative influence of these two factors will be important issues for further research.

Information Search and Organization

A second element important for online environments concerns the organization of information. For years, we have known that the organization of product information can influence choice. The standard rationale is that the organization of information can change the cost of searching for various types of information, which in turn can influence decision strategies (Bettman, Johnson, and Payne, 1990; Kleinmuntz and Schkade, 1993). Russo (1977) for example showed that reorganizing unit price information into lists that are sorted from cheapest to most expensive changed consumer choices in supermarkets. Can this happen in the virtual shopping environment?

Lynch and Ariely (1998) created online wine stores that manipulated the processing cost of three kinds of information: (1) price, (2) quality, and (3) the ability to compare between different online stores. They found that price sensitivity was highest when price was easy to process, but quality information was difficult to process. In contrast, when quality

information was easily generated, this attribute grew in importance resulting in reduced price sensitivity. Moreover, when actually given the wines for later consumption, subjects reported that they were happier with the wines purchased in the environment with easy access to quality information. Lohse and Johnson (1998) report similar results examining choice of disposable cameras and cookies.

The revolutionary power of the online environments is that the display of information is very malleable, and under the control of the seller, buyer, or both. Peapod, for example, allows customers to sort for themselves on a variety of attributes. A health conscious consumer can sort products based on fiber or sugar content, for example, and a bargain hunter can sort on unit price. In contrast, we could easily imagine a retailer who allows sorting only on attributes for which they excel or those that give them a competitive advantage. From a research perspective, it is even more important to understand the impact of environmental contexts on product search.

Product Evaluation

Many product categories are not easily decomposed into constituent, Lancasterian features. For example, choices among movies, novels, fine art, and perhaps even homes, do not seem satisfactorily described by a small set of features common to all alternatives. When faced with these decisions, consumers often turn to others for advice. Consumers listen to critic opinions when deciding which movie to go see, discuss the books they read with friends and co-workers, and rely on an agent to find a new home. In other cases, the number of alternatives that are available is immense, and with electronic environments, we suspect growing. For example, Amazon (www.amazon.com) claims to have available over 3 million titles, and CDNow (www.cdnow.com) carries over 300,000 CDs, cassettes, vinyl albums, music videos, laserdiscs, DVDs, movies and T-shirts—ten times the size of the average music store.

The problem faced by consumers in these environments is serious. On the one hand, for decomposable products, search costs can lead to an increased reliance on satisficing instead of optimization. Or these high variety product sets can cause consumers to delay purchase, not only because the complexity of the choice set is high, but also because consumers are uncertain as to the set of possible options (Greenleaf and Lehmann 1995).

For non-decomposable products, the situation is more serious to the extent that an online environment can potentially rob one of important experiential information. Such environments limit one's ability to ask a trusted friend her opinion of a movie, or to ask a store clerk how a novel compares to the author's prior work. Currently, E-bay (www.ebay.com) solicits users to provide self-reports of experiences with vendors as a means of building credibility and trust. Numerous movie and restaurant review sites, as well as online booksellers use similar self-sustaining mechanisms. To the extent that people find layman reviews informative and credible they may turn to these alternative sources of input instead of agent services. However, it is not clear how a user can directly establish the credibility of this information. Witness, for example, the recent controversy over Amazon's decision to put "preferred advertisers" and the top of its recommendation lists. The growth in virtual

communities and use of collaborative filtering techniques to help identify like-minded users may be a direct response to consumers' need for experiential information and advice. Thus, electronic environments can be expected to replace small numbers of personal reviews with pooled recommendations from a large number of like-minded consumers.

Thus a major consideration in developing good online shopping environments is to provide tools to help solve these problems. We suggest that help is needed on at least three fronts: First, people need assistance in preference construction and discovery. Second, they need help finding and organizing relevant information. Finally, help is needed in evaluating attractive alternatives and executing decision strategies.

Agents to the Rescue?

The traditional definition of an electronic agent is a software program that "knows" users' preferences and can act autonomously on their behalf (Maes 1995). These systems typically require consumers to engage in an interactive process that involves sharing information, performing tasks consistent with the user's goals, and monitoring responses in order to learn how to improve performance. Given our concerns about consumer decision making in online environments we will examine how electronic agents might address some of these problems.

Of course, agents are not a new development (Solomon 1986). Consumers have used human agents, such as realtors, financial analysts, and interior decorators, to assist them in their buying decisions or to act on their behalf long before the advent of the electronic marketplace. Interestingly, Reeves and Nass (1998) have demonstrated that people tend to interact with computers in a manner similar to how they interact with other people. Therefore, by examining the various benefits that human agents offer we hope to shed light on the features that one would want to incorporate into electronic agents.

Roles Agents Perform

Human agents are turned to for their expertise and advice as well as trusted to act as surrogates who save us time and reduce cognitive effort. Similarly, the ideal electronic agent would serve a variety of functions (see Table 1). Agents can act as tutors who inform clients about the most important factors to consider when evaluating alternatives within a product category, and to assist their clients in discovering their preferences. For example, a good physician will not only treat her patients' symptoms, but also acquaint them with how to improve their diet and lifestyle to maintain good health.

Agents can act as clerks who save us time and effort by screening out unattractive alternatives. In addition, they can provide access to otherwise closed markets, and facilitate transactions between parties. For example, many interior decorators have direct access to merchants and manufacturers that are not readily available to consumers. Similarly, a realtor's job does not end once he has found his client the perfect house. The agent will

Table 1. Role of Agents in Consumer Decision Making

Consumer Decision Making Tasks	Roles of Agents	Description
Preference Construction and Discovery	Tutor	Agents may educate a client about the features available in the category and help uncover client preferences.
Information and Alternative Search	Clerk	Agents may assist clients in performing tedious tasks such as information search and product screening.
Product Evaluation	Advisor	Agents may be called upon to express their expert opinion, or to provide advice tailored to their client.
Purchase	Banker	Agents may negotiate on their clients' behalf and facilitate the purchase of products and services.

often help with many of the details required to close the sale and may be called on to help find a good plumber or electrician.

One of the primary roles of a human agent is to act as an advisor and provide guidance to a client. For example, a financial analyst is expected to offer sound advice regarding the appropriate portfolio mix to ensure that a client can achieve specific long-term financial objectives. Sometimes agents are called upon to negotiate the terms of a purchase on a client's behalf, and thus take on the role of banker.

The various roles that an agent can perform all require building trust. The belief that another will act as an advocate and pursue what is in the best interest of a client is necessary for the success of agency. In the various arenas where professional agents are commonly relied on, laws have been instituted to protect the interests of the public and prevent these individuals from taking advantage of their clients. In fact, in certain arenas society has deemed that individuals *must* use an agent to act on their behalf. Only a doctor can prescribe drugs, and it is a lawyer's task to represent us in court. Looking forward, it is likely that the same kinds of laws and institutional norms that protect people from abuse from human agents will develop for electronic ones.

Goals of an Electronic Agent

Our examination of consumer decision making in electronic environments and our consideration of the various roles that human agents play serves as a useful starting point for establishing a set of goals for electronic agents. These goals are summarized in Table 2. We will briefly elaborate on each of them.

Improving Decision Quality

There is enormous potential for electronic agents to assist users in navigating electronic environments and improving the quality of the decisions we make. Our discussion will parallel the roles of human agents described in Table 1.

Table 2. Goals of an Electronic Agent

Goal	Features
Improve decision quality	<ul style="list-style-type: none"> • Assist consumers in learning about the product category and preference discovery • Reduce decision complexity • Be a clearinghouse for good information • Provide an appropriate consideration set for evaluation • Adapt over time in response to new information and feedback
Increase satisfaction	<ul style="list-style-type: none"> • The system should be flexible and responsive to a user's requests • Increase the match between consumers' taste and the products they get • Simple to operate and user-friendly • Eliminate tedious work and allow the consumer to experience the "fun" • Set realistic expectations
Develop trust	<ul style="list-style-type: none"> • The agent must work to satisfy and protect the users' best interests • Provide reassurance the user is getting the "right product" for a reasonable price

Agent as Tutor. What is the ultimate goal of an electronic agent? If the goal is to improve consumer's decision making then it is very important that the agent can assess an individual user's familiarity with the product category and respond appropriately. Given the evidence that preferences are often constructed on the spot rather than reflecting a well-formed utility function one can not take for granted that users are able to articulate their true preferences directly. The fact that preferences are largely constructed suggests that measuring them is best viewed as a form of architecture (building a set of useful or defensible preferences) than as a form of archeology (uncovering preferences that are already there) (Payne, Bettman, and Schkade, in press).

The job of eliciting a user's preferences in order to provide a product recommendation is also not a simple task. Consider the following thought experiment. Suppose a (perverse) benefactor has decided to give you a laptop computer. Rather than allowing you to choose a particular model, she requires you to select between various ways to project your values and then used a machine to select the item with the highest score given these values. You can select from among four preference elicitation mechanisms. A model built from: (1) your past computer choices in the marketplace, (2) a series of hypothetical choice sets, (3) a ratings-based conjoint task, or (4) your self-explicated ratings of the importance of product attributes.

Thinking about this task makes it clear that eliciting consumer preferences is not a simple task. The first two options, which are both choice-based, are appropriate for a user who is quite familiar with, and has practiced making decisions in the product category. A good example of how these two preference elicitation methods can fail is the in-store movie recommendation system called Take10, which Blockbuster recently tested. This system provided customers with a list of ten video recommendations based on the individual's previous rental history. However, the system never collected data indicating what the customer actually thought of the movie after viewing and did not control for multiple family members using the same card. Not surprisingly, the system failed to

achieve customer acceptance and was withdrawn. The critical lesson here is that past choices may be inappropriate to use to predict future desires, thus, particularly in categories where people are prone to err in predicting their own tastes, it is important to collect post-consumption feedback as well as choice.

There are, however, situations in which a choice-based elicitation method might be appropriate. For example, when commitment from the consumer is an important part of the desired outcome. This may be one of the reasons contemporary society gives the individual the right to choose a mate, and parents allow children to make their own choice of college. Making the choice increases the likelihood that the choice will last due to personal commitment.

The second two preference elicitation methods are both ratings-based. These are more appropriate for the inexperienced consumer, for a product category containing novel products (artwork), or for infrequently purchased durable products (cameras). Both of these ratings-based tasks require considerable effort on the part of the user, but offer the opportunity to learn about features of the product category as well as one's personal preferences. The trade-off between the collecting additional information so the system can learn and improve its performance and the increased workload for the user is a difficult one to resolve. Avery and Zeckhauser (1997) point out the welfare problems associated with encouraging individuals to share information for the betterment of a community of users. They predict that incentives will be needed to prevent free riders from benefiting from the goodwill of others. Even if the user is the direct benefactor of the effort, it may be difficult to motivate individuals to participate in an exchange of information.

One of the earliest electronic recommendation agents was Agent Inc.'s "Firefly" site. This system offered users personalized recommendations for movies and music. Personal profiles were built by having users provide evaluations of movies they had already seen, or songs they liked. The developers used a "collaborative filtering" technique to identify like-minded users within its online community. The system's recommendations were based on the input from like-minded users. Today, several companies have deployed collaborative filtering methods to provide personal recommendations for books (www.amazon.com and www.barnesandnoble.com), music (www.launch.com), web sites (my.yahoo.com), and software (my.ZDNet.com). While collaborative filtering offers a relatively painless way for users to communicate their preferences and an effective means for developing useful product recommendations it cannot provide users insight into the drivers of their preferences (Gershoff and West 1998). A consumer who is unaware of the why he likes or dislikes an alternative will remain dependent on the agent to provide him with good recommendations, or worse, may continue to make bad choices in the future. If, on the other hand, a consumer actively works with the agent in the determination of preferences, he not only learns things about himself, but that kind of collaboration encourages the customer's buy-in and ultimate satisfaction with the choice (Kahn and Huffman 1998).

The foregoing suggests that consumers may require additional guidance, particularly in complex product categories, to help them understand the important features to consider when evaluating product alternatives. Unlike human agents, electronic agents tend to be outcome-focused (interested in providing good recommendations or finding all the sites that match a user's query) rather than process-focused (aiding the user in understanding the

category and why a product fits the person's needs). Incorporating a tutorial component into an electronic agent that encourages users to articulate and understand their values would provide numerous benefits to the consumer (Keeney 1992). An interesting parallel can be made to the study of human learning where it has been shown that people have difficulty learning relationships without the help of cognitive feedback that informs them about the structure of the environment (Balzer, Doherty, and O'Connor, 1989). An educated consumer is more likely to choose the best product, and is therefore less likely to experience dissatisfaction in the consumption experience (West, Brown and Hoch 1996).

Agent as Clerk. Facilitating preference discovery and accurately eliciting user preferences are important goals to consider when building an electronic agent system. However, in some instances users are looking more for the information that an agent can provide than advice. Search engines are good examples of this. These systems perform the tedious task of searching for information or alternatives that fit within a client's specifications. However, a focus on simply providing relevant information may not lead to good decisions (Ackoff 1967). This is particularly true for consumers who are inexperienced with the product category (Chase and Simon 1973). Information-overload, even when the information is "good," may lead to sub-optimal decisions (Malholtra 1982; Ariely 1998). As stated earlier, while technology allows for an unlimited amount of information to be made available, our cognitive capacities have not changed and humans can only process a limited amount of information effectively. This suggests the need for finding ways to condense information into a form that is easier to process. An alternative by attribute table, for example, can be parsed much more efficiently and ultimately cause less confusion to the customer than serially presented alternatives (Huffman and Kahn 1998).

Sometimes consumers want advice that goes beyond the information they explicitly asked for. In these cases the electronic agent needs not only to search for the information that was requested by the consumer (clerk) but also to incorporate an advice giving mechanism and information filtering. PersonaLogic (www.personalogic.com) is designed to assist buyers in finding the perfect automobile or making travel plans by querying the user about the product features sought, then filtering out "unacceptable" alternatives. Similarly, Realtor.com is designed to help a potential buyer to screen homes that are currently for sale. The approach that both these systems adopt is quite efficient for users who are familiar with the product category and have a clear idea of what they are looking for. A user interested in scanning Realtor.com's database of over 100,000 homes nationwide is asked to define the neighborhood(s) being considered, an upper limit on price, the minimum number of bedrooms and bathrooms acceptable, etc. The system sequentially presents alternatives that fit the user's specifications. Past research, however, has shown that using attribute cut-offs to screen alternatives tends to result in inferior product decisions due to inadvertent product elimination (Widing and Talarzyk 1993). This issue is particularly troubling in an agent context where the user may never be exposed to truly preferred alternatives because the system has eliminated them from consideration. Information filtering problems can be addressed by using "fuzzy" models that allow for uncertainty in the reporting of attribute cut-offs and/or by using collaborative filtering

methods to incorporate information from like-minded users. The problem of false confidence in the search method suggests that agents need to include a monitoring system that enables them to test the degree of optimality of the choices made.

Agent as Advisor. In designing a system to provide consumers with personalized recommendations there are at least two competing goals operating. One goal is to provide a user with alternatives that are likely to be most desirable. Another important goal of the system is to learn and update its model of a user's preferences. Typically, each presented item is chosen to maximize its marginal probability of selection. In fact, many search engines sort Internet sites and some report the estimated selection probabilities. An open issue that arises from this approach is "What is the appropriate set of items to present?" Consider an Amazon visitor searching for a new book. In this case, showing all books with highest estimated selection probability is most likely to achieve this goal, yet there are drawbacks from both the agent's and user's point of view. For the agent, what learning about the user can take place? If the user selects a book the agent already "expected," then the agent's learning is minimal. Since the only shown books are those most likely to be picked, which are highly correlated with each other, there is little opportunity for the agent to be "surprised," and therefore learn. For the user, there is little opportunity to broaden one's consideration set as she is shown only those items most consistent with past behavior. If we believe that people desire variety (McAlister and Pessemier 1982, Kahn 1995), and/or become satiated with certain types of choices, then an intentionally broadened alternative item selection mechanism may be beneficial. Such issues have previously been considered in diverse areas such as educational testing, optimal item selection in Computerized Adaptive Tests (Wainer and Mislevy, 1990), and experimental conjoint design, Adaptive Conjoint Analysis (Green, Krieger, and Agarwal 1991). In both cases, selection algorithms are designed to optimize information from the agent's perspective; the education of the user is not considered. However, such theory would provide a good starting point for research in optimal presentation sets for agents.

Two options are promising: (1) the system could show the user a set of alternatives that is a blend of most preferred alternatives and those which will provide the most information for the system (how to select these is an open issue), or (2) the system could ask the user a priori if the purpose is a single item search or learning about new alternatives. The idea of querying the user about intent has the added benefit of reducing the risk of misinterpreting behavior when the user is engaged in choosing a product for someone else. The social dimension of buying for someone else, as occurs in gift selection creates yet another challenge for interpreting behavior. Amazon added a "Gift Recommender" to aid its customers in this difficult task. A side benefit of this system is that it prevents misinterpreting an unexpected purchase (one that does not fit with a user's personal history) as a change in preference. Clearly, the optimal presentation set and interpretation of a user's response will depend on the current goal.

Improving consumer decision quality will require continuous monitoring of a user's preferences and responses over time. Consumer needs change in response to life events and situational factors, such as the birth of a child or a new job. In addition, consumer preferences evolve over time as more experience is gained in a product category. For

example, an inexperienced wine drinker will favor the sweetness of Riesling to the density and richness of white Burgundy. However, as the individual's tastes develop he will come to appreciate the layers of buttery and citrus notes of the white Burgundy. This poses a challenge from a modeling perspective. How does the system detect changes in a user's behavior? How should the model weight old versus new observations? The solution to the problem is likely to require that the model regularly test itself by either asking the user to evaluate some unfavorable alternatives, or recommending unacceptable alternatives.

Many open issues exist regarding the generation of inferences about users by agents. One can separate these concerns into two areas: data and modeling. Regarding data, we see the main issues as: (1) how to summarize potentially massive amounts of information to allow predictions in real time, (2) how and when to let "old information" expire thereby refreshing the system, and (3) when to actually "stop" collecting information as user uncertainty is minimal. Summarizing users inputs/choices by a small number of informative but only partially sufficient statistics, which are updated by adding new information and dropping old ("creating a fingerprint") has been used in other areas (such as fraud detection for the phone company) and may be an area to pursue.

When modeling data to generate predictions, there are a number of research opportunities. First, data collected from an individual may be of many forms; e.g. choice, survey, and experimental studies. This is especially true given the possibility of using electronic agents to query users in multiple modes, and or obtain individual information from other sources. Therefore, how do we build "supermodels" which allow for incorporating and combining of seemingly uncongenial information? Secondly, recent research in collaborative filtering (Gershoff and West 1998) has suggested that when modeling or predicting individual preference, the utilization of other user's responses may play a significant role (i.e. add information) even after conditioning on the features of the products. So developing models that incorporate product features and community knowledge to determine predictions for an individual user looks promising. Thirdly, models which present alternatives to users, and record which ones are selected are in fact collecting one additional piece of information; those options not selected. That is, there is information in seemingly missing data (Little and Rubin 1987) in that those ratings unobserved are likely to be lower, as they were not selected. Current collaborative filtering techniques do not incorporate this information. Finally, as with the data storage issues, these models will need to be implementable in real time, which is a rather daunting task.

Agent as a Banker. After the selection has been made, the final role of the electronic agent is to take care of the final transaction. This part is concerned mainly with financial transactions and encompasses within it two main functions. The first function is to select the vendor, supply, and payment terms. The second function is to transfer payment and finalize the transaction. In order to accomplish the first function an agent can search all the potential vendors, and negotiate with them for appropriate terms (see Pazgal and Vulcan 1998). An example for such a system is currently tested by British telecom, where an agent negotiates in real time with different long distance carriers for price and bandwidth and uses the best alternative for any particular call. Unlike the other aspects of agent roles we

discussed, this aspect concerns only agent-agent communication and no human-agent dialog.

Increasing Consumer Satisfaction

While one would expect that a natural outcome of improving consumers' decision quality is increased overall satisfaction, however, this may not be the case. When measuring consumer satisfaction it is useful to consider both satisfaction with the decision *process* as well as with the final choice (Fitzsimmons 1996; Fitzsimmons, Greenleaf, and Lehmann 1997). Just as the human component of any service exchange will impact a consumer's evaluation and future buying behavior, the interface of an electronic agent will directly affect a user's satisfaction with the decision process. Agents can make a client feel good about the process even if a poor choice is ultimately made (Widing and Talarzyk 1993). This is particularly true when there is a substantial probabilistic component associated with the outcome. For example, a financial analyst might recommend purchasing a stock that winds up being a bad investment. Because most consumers know that the market is very difficult to predict they may not hold the analyst accountable for the loss, if the decision process was managed appropriately.

Flexibility and Responsiveness. A variety of steps can be taken to increase consumer satisfaction with the process and final choice. Electronic agents have the unique ability to allow for personalization. Allowing the user to control the system to meet her personal needs will increase personal satisfaction (Gilmore and Pine 1997). PointCast (www.point-cast.com) is an interesting example of this. This screensaver delivers up to the minute news stories, stock prices, weather forecasts, and sports scores round the clock. Users are allowed to specify the type of information they are most interested in and to personalize the interface. It is also important to minimize the start-up costs associated with using the agent. Microsoft's "intelligent" agent, the paper clip, was specifically designed to anticipate a user's needs and offer assistance to reduce learning costs. Further it adapts to the usage patterns of the user, providing training that is appropriate to the user's current expertise.

One of the primary benefits an electronic agent can offer is to reduce the amount of tedious work the user needs to perform in the process of finding the information or product of interest. This may be as simple as storing user information, such as name, address, etc. for future visits so that the person does not have to continually provide the same information. However, this raises concerns about how this information will be used. Today many sites use the information collected in the form of cookies to personalize ads and other information on the user's screen when the user revisits a site. The primary reasons for Microsoft's recent acquisition of Firefly was because of its privacy technology that allows users more control of their personal information on the Internet in anticipation of consumer backlash from collection of clickstream data.

Managing Expectations. Managing consumer expectations is also an important factor to consider in the design of electronic agents. Early on, when the system has little information

to work with, the recommendations it provides may not suit the user well. Thus the users might lose faith in and stop using the system unless this is clearly communicated up front. One method of dealing with this problem is to collect enough demographic and background information to establish reasonable priors using collaborative filtering. MovieCritic (www.moviecritic.com) is a good example here. This agent will not recommend a movie until the user has rated at least twelve films and answered a battery of questions. If the user understands the importance of sharing information to improve the system's performance then he is more likely to be forgiving of mistakes early on. In addition, to managing consumer expectations regarding the agent's performance, it is also important to set realistic expectations of the product. One of the potential downsides of working with an agent that educates the user and presents a set of alternatives consistent with the user's specifications is that it forces the person to make difficult and unpleasant tradeoffs that might have gone unnoticed otherwise.

Increasing returns to scale associated with dealing with a single agent over time tend to create switching costs for the user. The more I use an agent, the more data the agent has on my tastes and, therefore, the better that agent can act on my behalf. In order to use another agent I will have to train it about my preferences. This feature invests electronic agents with a powerful loyalty enhancing property that is likely to keep users returning to site-specific agents. It also suggests a counterargument against the contention of friction-free capitalism on the Web.

Developing Trust: Who Does the Agent Work For?

The final and arguably the most important requirement of a successful agent is that it develop and maintain trust (Urban 1998). Electronic agents are not fundamentally different in needing trust from humans and institutions in other aspects of commerce. Consider companies involved in relationship marketing with their partners, technical sales forces engaged in consultative selling, or brand managers defending the credibility of a brand. In these cases, problems of electronic and human agents are very similar.

Three dimensions of trust arise particularly in the context of electronic agents. First, trust is needed so that the consumer is willing to give information to the agent, either in the form of access to resources (e.g., a credit card number), or in the form of personal information (e.g., magazine readership). Clearly, legal and infrastructure changes will have to develop to assure confidence in this critical component of electronic commerce. A second trust dimension constitutes the belief that the agent acts in the best interest of the customer. This trust is not absolute, but relative to expectations. For example, a reasonable expectation of a retailer's site (such as Amazon) is that it will find the best books regardless of their profitability margins for the company. However, each retailer is expected to promote its own offerings and thus is not held to the standards of a search across competitors expected of an independent agent such as Bargain Finder. The third trust dimension involves the belief that the good intentions of the agents actually result in appropriate choices. This requirement was vividly illustrated in the failure of Blockbuster's Take 10 product. Providing poor suggestions may be worse than no suggestions at all.

How is trust developed? Urban, Sultan, and Qualls (1998) suggest that trust-building cues play a role. They consider the context of an online store with a shopping advisor, represented as a person with a pictorial image and name. Three classes of trust building cues are proposed for investigation. The first group has to do with the site: issues such as privacy (e.g., no cookies), security of payments, and endorsements. The second deals with the shopping advisor and the advice given, for example: friendliness and warmth, unbiased data, and acknowledgment of weaknesses. The third group enters the process at the fulfillment stage and includes ease of ordering and payment, keeping promises, delivering on time, and avoidance of billing errors. Taken together this research offers a framework for studying the effect of cue characteristics on the building of customer confidence and trust.

Additional research opportunities abound for testing ways to develop and preserve these dimensions of trust. First, there is the issue of the *transparency* of the agent's method. While collaborative filtering may produce good choice options, it is important to test various ways that the process can be explained to, and understood by consumers. Second, there is the related issue of *control*—the perception that the consumer controls the agent rather than the reverse. This need for control suggests that it would be valuable for agents to ask screening criteria, and collect feedback on the desirability of suggested offerings. Third, there is the issue of *framing* the agent's recommendations. For example, should less valuable alternatives intentionally proceed the most desirable choice to increase its perceived value? Finally, research is needed into the patterns by which some types of businesses have natural advantages with respect to trust. For example, a customer may be more likely to trust a doctor or a bank with personal data than a supermarket (Hagel and Rayport 1997).

Notice that these research questions can be more easily answered in the context of electronic agents than for individuals or organizations. The processes by which electronic agents reinforce trust can be precisely defined in the programmed code, thereby minimizing noise created by human and organizational factors. This greater control of the manipulations, combined with the ability to efficiently test strategies on many people simultaneously, leads to the prediction that theoretical and practical knowledge of trust will blossom through studies of electronic agents.

Note

1. This working paper is based on the "Agents and Environments" session of the 1998 HEC Invitational Choice Symposium. Please refrain from quoting or reproducing this document in whole or in part without the consent of the authors. Suggestions or feedback should be forwarded to the corresponding author: Patricia M. West, Associate Professor of Marketing, Fisher College of Business, The Ohio State University, 2100 Neil Ave., Room 544, Columbus, OH, 43210; e-mail: west@cob.ohio-state.edu.

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