Interactive Consumer Decision Aids

Chapter for publication in the forthcoming Handbook of Marketing Decision Models (Springer Science + Business Media)

Kyle B. Murray & Gerald Häubl

Author Bios:
Kyle B. Murray is the F.W.P. Jones Faculty Fellow and an Assistant Professor of Marketing at Western Ontario University's Richard Ivey School of Business, in London, Ontario. Gerald Häubl is the Canada Research Chair in Behavioral Science, the Banister Professor of Electronic Commerce and an Associate Professor of Marketing at the University of Alberta, in Edmonton, Alberta. The authors can be reached at kmurray@ivey.uwo.ca and gerald.haeubl@ualberta.ca.

Acknowledgements:
The authors gratefully acknowledge the research funding provided by the Social Sciences and Humanities Research Council of Canada. This work was also supported by the F.W.P. Jones Faculty Fellowship held by Kyle B. Murray and the Canada Research Chair in Behavioral Science and the Banister Professorship in Electronic Commerce held by Gerald Häubl.

Too Much Choice for Consumers?

Today's consumers are faced with a vast and unprecedented breadth and depth of product alternatives: a Wal-Mart Supercenter stocks over 100,000 items [Yoffie 2005], Home Depot more than 50,000 [Murray and Chandrasekhar 2006], and the typical grocery store more than 30,000 [Schwartz 2005]. The advent of online shopping has further increased the choices that are available to consumers; both eBay.com and amazon.com offer literally millions of unique products, from thousands of product categories, for sale through their websites. If deciding among all of these alternatives gives consumers a headache, a trip to the local pharmacy does little to relieve the pain. Even in product categories that one might consider relatively simple and straightforward, such as analgesics, it is common to find in excess of 60 different varieties side-by-side on the shelf [Schwartz 2005]. The consumer is asked to select the chemical composition (ibuprofen, acetaminophen, acetylsalysic acid, etc.), decide between brand names (Advil, Tylenol, Aspirin, etc.) and generics, and choose from numerous features ("cool burst," coated, time release, etc.), packaging (liquid gel, tablet, caplet, as well as the number of pills, etc.) and concentrations (regular, extra strength).

For the consumer, there is a cost to processing information, and that cost rises as the complexity of the decision increases [Shugan 1980]. As a result, making decisions in a world with an ever-growing variety of products and product categories is increasingly taxing. Traditionally, humans have been able to effectively adapt to complex environments by adjusting their decision making strategies to the situation they are faced with [Payne, Bettman and Johnson 1993], employing heuristics to lighten the cognitive load [e.g., Kahneman and Tversky 1984], or simply doing what they did last time [Hoyer 1984; Murray and Häubl 2007; Stigler and Becker 1977] to arrive at a satisfactory, if occasionally suboptimal, decision [Simon 1955, 1957].

In fact, we are relatively adept at trading off the effort we expend to produce the results we require. Nevertheless, as the number of choices and decision complexity increase, our ability to efficiently make good decisions is compromised. The additional constraints of time pressure and the many demands upon us beyond consumption decisions (e.g., work, family, etc.) only exacerbate the problem [Perlow 1999; Perlow, Okhuysen and Repenning 2002]. In fact, there is growing evidence that the cumulative effect of all the choices that must be made on a regular basis cause consumers substantial (di)stress [Schwartz 2005; Mick, Broniarczyk and Haidt 2004]. In this chapter, we examine the current state of a set of tools that have the potential to assist consumers in their decision making by improving the quality of the choices they make while simultaneously reducing the effort required to make those decisions. We refer to these tools as *interactive consumer decisions aids* (ICDAs).

The Paradox of Choice

Decades of psychological research have demonstrated that having a choice among alternatives is better than having no choice at all. Specifically, we know that the freedom to choose increases intrinsic motivation, perceived control, task performance, and life satisfaction [Deci 1975, 1981; Deci and Ryan 1985; Glass and Singer 1972a, 1972b; Langer and Rodin 1976; Rotter 1966; Schulz and Hanusa 1978; Taylor 1989; Taylor and Brown 1988]. In addition, it appears that consumers are more attracted to vendors that offer more choice through a greater variety of products [Iyengar and Lepper 2000] and products with more features [Thompson, Hamilton and Rust 2005].

However, recent research has revealed that too much choice can, in fact, have adverse consequences. This work suggests that choosing from among a large number of alternatives can have negative effects, including increased regret, decreased product and life satisfaction, lower self-esteem, and less self-control [e.g., Baumeister and Vohs 2003; Carmon, Wertenbroch and Zeelenberg 2003; Schwartz, Ward, Monterosso, Lyubomirsky, White and Lehman 2002].

For example, in a series of field and laboratory experiments, Iyengar and Lepper [2000] compared the effects of choosing from a small versus a large number of alternatives. All else being equal, they found that shoppers were significantly more likely to stop to sample products when 24 were on display (60%) than when only 6 were on display (40%). However, when it came to actually making a purchase, only 3% of those in the extensive choice condition (24 products) bought one of the products, while 30% of those in the limited-choice condition (6 products) made a purchase. In a follow-up study examining chocolate consumption, the same authors replicated previous research when they found that consumers prefer to have the freedom to choose what they are consuming. Specifically, they found that people are more satisfied with the chocolate they eat when they are able to select it themselves, as compared to being given a chocolate randomly selected from the same assortment. However, they also found that people choosing a chocolate from a limited selection (6) were significantly more satisfied with their choice than those choosing from an extensive selection (30). It seems that, although people like to have the freedom to choose what they consume, and are attracted to larger product assortments, they are more likely to make a purchase and be satisfied with it when the choice is made from a limited number of alternatives.

Similar results have been found by researchers studying the optimal number of product features. Advances in technology have not only allowed retailers to offer consumers an ever-increasing number of products, they have also allowed manufacturers to load products with a growing number of features. Take, for example, today's cell phones that include the capabilities of a gaming console, text messaging device, wireless internet, calendar, contact organizer, digital camera, global positioning system, and MP3 player; in addition to its multiple telephone functions. Although each of these features are individually useful, when combined in large numbers they can result in an effect known as "feature fatigue" [Rust, Thompson and Hamilton 2006; Thompson et al. 2005]. When consumers are deciding which product to buy, they tend to focus on the capabilities of the product (i.e., what it can do); however, their satisfaction with the product, once it has been purchased, is driven mostly by how easy it is to use [Thompson et al. 2005]. Ironically, consumers prefer to buy products that have many features and, as a result, they are less satisfied with their choices. Consequently, this dissatisfaction decreases the vendor's long-term profitability [Rust et al. 2006].

Interestingly, Schwartz et al. [2000] find that the negative effects of too much choice are most acute when people attempt to find an optimal product – i.e., when they act as maximizers. For example, a consumer looking for the perfect cell phone will tend to be less happy, less optimistic and less satisfied, as well as lower in self-esteem, than someone who is just looking for an adequate phone. Even at a more general (societal) level, there is evidence to suggest that too much choice is decreasing happiness, increasing incidents of depression, and potentially having a negative impact on moral development [Botti and Iyengar 2006; Mick et al. 2004; Schwartz 2005].

It seems counter-intuitive that fewer choices are better. Why would we want to limit our options and opportunities? Yet, it is becoming apparent that there are benefits to having some constraints on the number and complexity of the choices that consumers have to make. Do we really need (or want) to choose from more than 60 types of pain relievers, 175 varieties of salad dressing or 85 different home telephones [Schwartz 2005]? Maybe not. Yet, when we have a headache, it would be nice to have pain relief that was the best available for our own unique physiology. In fact, although people generally do not want to sort through a vast selection of salad dressings or telephones (or, for that matter, most products), rarely would consumers object to having a small number of options that are ideally suited to their particular preferences. Similarly, we would like to buy products with the capabilities that we need, and avoid the features that add complexity without increasing usefulness. In other words, most consumers would like to make better decisions with less effort. This is the promise of ICDAs.

Building Interactive Consumer Decision Aids (ICDAs)

We define ICDAs broadly as technologies that are designed to interact with consumers to help them make better purchase decisions and/or to do so with less effort. Fortunately, recent advances in information technology have made the development and implementation of such tools a realistic ambition. In fact, examples of effective ICDAs are becoming a part of everyday life for many people. Take, for instance, internet search engines, in-car navigation systems, personal video recorders (e.g., TiVo), and RSS feeds (e.g., for news and coupons). In fact, it has been argued that humans are at the beginning of a transition to a world of augmented reality – wherein the real world is augmented by computer-generated ("virtual") stimuli – that offers substantial assistance anywhere at any time [Abowd, Mynatt and Rodden 2002; Weiser 1991, 1993]. For example, together with the physical traffic environment, the electronic maps and context-sensitive assistance built into a vehicle's navigation system can be viewed as creating an augmented driving reality.

Unfortunately, these (emerging) technologies have not been harnessed for the purpose of consumer decision support. Early attempts at creating ICDAs, in the form of electronic recommendation agents [Häubl and Trifts 2000], such as personalogic.com, were unsuccessful, and they may even have incited some resentment on the part of consumers [Fitzsimons and Lehmann 2004]. Currently, the vast majority of systems that could be considered ICDAs are aimed exclusively at personalization in an e-commerce setting (e.g., amazon.com's Goldbox) or are focused on price search (e.g., mysimon.com, pricegrabber.com or shopzilla.com). Although useful under some conditions, these tools are highly constrained and fail to live up to the full promise of ICDAs. In the sections that follow, we review the research that has led us to our current understanding of the significant potential of ICDAs to assist consumers in their decision making, and we discuss a number of reasons why this potential remains unrealized.

Interactive Shopping: Agent's to the Rescue?

The development and adoption of new technologies, such as the internet, has opened the door to new kinds of exchanges between buyers and sellers. For example, buyers have fewer constraints on search and comparison shopping. Rather than drive across town to obtain some information about a particular product (e.g., its price), consumers are able to access a wealth of information at the click of a mouse. In the extreme, such a marketplace has the potential to spark a dramatic rise in the amount of search that consumers undertake before making a purchase decision, which could result in substantial downward pressure on prices [Bakos 1997].

Alba, Lynch, Weitz, Janiszewski, Lutz, Sawyer, and Wood [1997] suggested that, for this type of search to be feasible, a number of conditions would have to be met: (1) product information would have to be faithfully provided to consumers; (2) the set of available products would have to be substantially expanded beyond what local or catalogue shopping offered; and (3) search across stores and brands would have to be unimpeded. Importantly, these authors emphasized screening as the most critical determinant of the adoption of online shopping (see also Diehl, Kornish and Lynch 2003). By and large, the first and second conditions appear to have been fulfilled. Although the internet has created its share of new forms of fraud, online product information appears to be at least as reliable as its offline counterpart. In fact, the growth of online shopping has also seen a rise in novel methods of providing consumers with information about information; including website certifications and verifications (e.g., Verisign, Truste, etc.), reviews from other consumers that have experienced the product (e.g., Amazon, Bizrate, etc.) or ratings of buyers' and sellers' past performance (e.g., eBay, Better Business Bureau, etc.). It is also true that for most (if not all) consumers, online shopping makes substantially more products available than can be found locally or through catalogue shopping.

However, search across stores and brands appears to be "stickier" than originally anticipated [Johnson, Moe, Fader, Bellman and Lohse 2004]. Although, some pundits initially saw online shopping as the death of the brand[1], it has become apparent that consumers are at least as loyal online as they are offline [Johnson, Bellman and Lohse 2003; Brynjolfsson and

[1] For example: "The internet is a great equalizer, allowing the smallest of businesses to access markets and have a presence that allows them to compete against the giants of their industry." Jim Borland, Knight Ridder (1998); "The cost of switching from Amazon to another retailer is zero on the internet. It's just one click away." Thomas Friedman, New York Times (1999); "Shopbots deliver on one of the great promises of electronic commerce and the internet: a radical reduction in the cost of obtaining and distributing information." Greenwald and Kephart (1999).

Smith 2000]. In addition, even though competition is "only a click away," that is a distance many consumers are unwilling to travel [Johnson et al. 2003]. In fact, research indicates that once shoppers have learned to use one store's electronic interface, they are very reluctant to switch to other stores [Murray and Häubl 2007].

Consequently, the evolution of online shopping has underscored the need for something akin to a "personal electronic shopper" [Alba et al. 1997]. Large volumes of relevant information are available to shoppers, who are limited in their capacity to process that information, and indeed hesitant to switch between different electronic interfaces to collect it in the first place. Current technology can provide tools that excel at searching and sorting information, and providing the results to consumers through a consistent interface.

However, it is worth noting that the need for such tools is not limited to the online world. As we have already discussed, big box stores and improvements in manufacturing technology have generated staggering assortments in traditional retail settings for even the most mundane product categories. At the same time, current technology can place the necessary tools in the palm of the consumer's hand. In doing so, the shopper's reality becomes augmented. In addition to the shelves and aisles in front of consumers, small portable devices can provide access to a virtual world of information and advice. Such a scenario has led consumer researchers to try to answer a number of important questions, not the least of which are: What role can (and should) ICDAs play in the buying and consumption process, and how should these tools be designed?

Four Potential Roles for ICDAs

West et al. [1999] mapped out a useful preliminary framework for thinking about the role of ICDAs in consumer decision making. They suggested that there are four key decision making tasks in which an ICDA could assist consumers. In some cases, ICDAs are already fulfilling these roles. For example, the internet offers a number of price search engines that scour the web for the lowest price on a particular set of products. However, others remain largely theoretical at the present time. Below, we will consider each of these potential roles of ICDAs.

Clerking

First, the ICDA could act as a *clerk*, assisting consumers in their search for product information and alternatives. ICDAs acting as rudimentary clerks are relatively common on the internet today. For example, there are a number of "shopbots" that search for the lowest price on a specific product. Sites such as mysimon.com, shopzilla.com and froogle.google.com gather up-to-date information on tens of millions of products from thousands of stores[2]. You tell the site what you are looking for, and it provides you with a list of vendors that have it in stock, along with their prices. In some instances, sellers pay a fee to be listed at the top of the search results. In most cases, the shopper is also able to customize the list alphabetically by store, by price, by consumer ratings or other means. These shopbots do not actually sell or ship anything, they simply provide product information.

Other ICDA clerks are specialists that work in a particular product category. For example, Amazon's bibliofind.com searches millions of rare, used and out-of-print books to help consumers locate hard-to-find titles from a community of third-party book sellers. Similarly, computershopper.com, specializes in computers and related accessories. There are other sites, often called "infomediaries," that provide third-party product information and/or consolidate product information to assist consumers in their decision making. Examples of such sites include bizrate.com, cnet.com, and consumerreports.org.

Other examples include ICDA clerks that vigilantly watch for sales, or send coupons, relevant to products that an individual consumer has expressed an interest in. Early implementations of this idea are being tested using Really Simple Syndication (RSS) feeds, and related technology, to deliver coupons (and other information on product discounts) to consumers. Examples of such websites include monkeybargains.com, dealcatcher.com, and couponsurfer.com.

In the bricks-and-mortar world, robots using RFID (radio frequency identification) technology are being tested that could serve in a similar role. In Japan, NTT Communications has teamed up with Tmsuk to test an RFID-driven "shopping assistant robot" in a mall in Fukuoka [NTT 2006]. When at the mall, shoppers choose a store that they are interested in visiting using a touch screen mounted on the robot, who then navigates its way there. However, consumers also have the option of directing the robot over the internet from their homes (or elsewhere). For the remote consumer, the robot provides a view of the in-store environment using a camera and connects the shopper to the store's human clerks via videoconferencing. When the shopper selects a product or a human clerk makes a recommendation, the robot reads the product's RFID tag and displays the relevant informa-

[2] Even more common are general information search engines – e.g., Google, Live.com, Yahoo search, Ask.com, etc. – which could also be classified under a liberal definition of clerking.

tion (including price, features, options, etc.). The robot is also able to carry shopping bags and lock valuables up inside its safe.

Advising

Another role for an ICDA is that of an *advisor* that provides expert personalized opinions based on the decision aid's knowledge of the consumer's preferences. The critical distinction between the role of clerk and that of advisor is the degree to which the information and recommendations provided by the ICDA are personalized (i.e., driven by the tool's understanding of the consumer's personal preferences). A pioneer in this area is Amazon.com. Its website has built-in capabilities to make recommendations to consumers based on their past behavior (and the behavior of people like them). Repeat customers at Amazon are greeted with a list of product recommendations based on previous searches and purchases at the website. Moreover, regular customers have a tab designated as their own "store" that is populated with additional recommendations, as well as links to online communities, commentary and more, all personalized on the basis of the profile Amazon has developed for each individual customer. By default, Amazon records the behavior of each shopper and uses that information to make recommendations. However, the site also offers users the option of editing their profile by providing additional information on products that they own, products that they have rated and products that they are not interested in.

Another type of advisor ICDA is not associated with any particular store and shares some of the features of a clerk. These tools are similar to ICDA clerks in that they provide consumers with a list of products based on what the shopper tells the ICDA. However, the advisor elicits much more detailed input and, rather than simply supplying a list of available products, it makes recommendations that are personalized based on the preference information that the consumer has provided to it (myproductadvisor.com is an example of such a website). After arriving at the site, consumers are asked to select an advisor by product category (e.g., new cars, televisions, cell phones, digital cameras, etc.) and to respond to a series of questions about their personal preferences within that category. The advisor then provides the consumer with a list, complete with the latest product specifications and comparison information, which ranks products in order of attractiveness to that individual.

In the realm of augmented reality, the Metro Group is experimenting with a "store of the future" (future-store.org) that can adapt a bricks-and-mortar environment into a personalized shopping experience. Using RFID tags to identify individual shoppers and products, these stores employ technology to assist consumers in finding the products on their shopping list (like a clerk), as well as recommending products (e.g., wine to go with dinner, like an advisor).

Banking

West et al. [1999] also envisioned an ICDA that could act as a *banker*, negotiating on the consumer's behalf and facilitating the ultimate transaction. The Automated Teller Machine (ATM) is a familiar technology that assists consumers by providing banking information and allowing users to complete transactions without human assistance. However, this type of technology would not meet our definition of an ICDA, because it is not intended as a tool that can help consumers make better decisions with less effort.

In fact, there are few real-world examples of the ICDA as a banker. One notable exception is the automation of bidding in the realm of online auctions. Here, the tool helps to reduce the effort required to make good purchase decisions in a consumer auction. For example, eBay's "proxy bidding" system automatically places bids on a consumer's behalf, up to a certain price. Consumers are able to enter the maximum amount that they are willing to pay for an item when they begin the bidding process. This information is not shared with the market (i.e., other buyers and sellers); however, it is used by eBay to compare the consumer's bid to that of others bidding for the same product. The system then automatically places bids on the consumer's behalf, out-bidding others by a small increment, until the product is purchased or bidding exceeds the consumer's maximum willingness to pay.

In general, ICDAs are only beginning to test their potential as bankers. The current implementations are very rudimentary versions of what they could be. For example, ongoing research is investigating marketplaces composed entirely of ICDAs acting on behalf of their human masters to complete transactions from need identification through product brokering, negotiation, payment, delivery and post-purchase support and evaluation [e.g., Maes, Guttman and Moukas 1999]. In the future, such tools may be capable of creating dynamic relationships, forming buying coalitions to leverage economies of scale and/or seeking out new suppliers who are willing to manufacture products demanded by the consumers that the ICDAs are working for.

Tutoring

Another potential role for ICDAs is that of a *tutor* who assists consumers in preference construction and discovery [West et al. 1999]. For example, an ICDA might teach the shopper about the important attributes within a product category and/or help the consumer "uncover" his or her preferences within a particular domain. Note the important distinction between a tutor and an advisor: the advisor uses consumers' preferences to make product recommendations; the tutor helps the consumer form his or her preferences. In other words, when acting as a tutor, the ICDA does not assume that the consumer has a detailed knowledge of his or her own preferences and, instead, helps the individual determine what these preferences are [e.g., Hoeffler, Ariely, West and Duclos 2006].

Current examples of this type of ICDA are quite rudimentary. One exception is the website pandora.com. This website was created by the Music Genome Project™; a group that has assembled hundreds of musical attributes (or "genes") into a database that breaks songs down by everything from melody, harmony and rhythm to instrumentation, lyrics and vocal harmony. You begin by entering an artist or song that you like. Say, for example, that you start with Jack Johnson, which Pandora classifies as mellow rock instrumentation, folk influences, a subtle use of vocal harmony, mild rhythmic syncopation and acoustic sonority. Pandora plays a song by the selected artist (Johnson) and then moves on to other artists/songs that are similar. For any song that Pandora selects, the user can respond in a number of ways, including clicking links such as: 1) I really like this song – play more like it; 2) I don't like it – it's not what this station should play; or 3) I'm tired of this song – don't play it for a month. This input is used to refine the playlist going forward. The user can also guide Pandora by entering other artists and songs that s/he enjoys. With extended use, the ICDA learns about the user, but it also teaches the user about his or her own preferences. The tool exposes consumers to product alternatives that they may not have been previously aware of, yet are likely to be interested in buying, all based on the consumer's personal preferences. Clearly, this is a role for ICDAs that is still in its infancy. Nevertheless, given the large percentage of decisions for which people do not have well-defined preferences [Bettman, Luce and Payne 1998; Mandel and Johnson 2002; Payne, Bettman and Schkade 1999], it is an area ripe with opportunity for additional research and application.

Agent Algorithms

Having mapped out a set of roles that an ICDA can fulfill, it is useful to take a moment to discuss some of the approaches and algorithms that a designer might employ to create an effective decision aid. Potentially, ICDAs could be developed on the basis of a wide variety of techniques ranging from consumer-centric formats for displaying information to search engines to sophisticated preference models. At a general level, ICDAs face a fundamental tradeoff in the design of their underlying algorithms. Specifically, these tools aim to: 1) work effectively in real-time environments; and, 2) develop a deep understanding of the needs and/or preferences of individual consumers either by directly eliciting this information or unobtrusively observing their behavior over time. To the extent that the ICDA is designed to perform in real-time, complex and detailed algorithms that operate on comprehensive databases are (currently) unrealistic. Therefore, when designing such tools, developers must balance the efficacy of the algorithm with its need to react quickly during interactions with consumers. Below, we discuss a few common approaches and algorithms; however, an exhaustive account of ICDA designs is beyond the scope of this chapter.[3]

At a simple level, an interactive decision aid could be a list or matrix of product information that the consumer is able to interact with by changing the way that the list is sorted or the matrix is organized. The previously discussed mysimon.com allows for this type of functionality. Another example would be Apple's iTunes music store that provides a list of the day's top downloaded songs, which the user can refine by genre. The shopping carts used by most online stores would also fall into this category of simple ICDAs. At a more general level, the comparison matrix used in Häubl and Trifts' [2000] experimental shopping environment is an example of this type of decision aid.

More sophisticated ICDAs attempt to develop an understanding of a particular consumer's preferences and make recommendations to him or her based on that understanding. There are many potential approaches to modeling consumers' preferences for the purpose of identifying products that match these preferences. In general terms, we can classify these methods as having either an individual or collaborative consumer focus [Ariely, Lynch and Aparicio 2004]. In both cases, ICDA designers employ models that are aimed at maximizing the attractiveness (i.e., utility) of the recommended products to the consumer [Murthi and Sarkar 2003]. Those ICDAs that focus primarily on the *individual consumer* use behavioral observa-

---

[3] Readers interested in more detailed descriptions of different types of ICDAs, recommendation agents and recommender systems are directed, as a starting point, to Adomavicius and Tuzhilin (2005) and Montaner, Lopez and de la Rosa (2003).

tions (e.g., click-stream search data or purchase histories) and/or explicitly elicited responses (e.g., attribute rankings or ratings) to develop a model of a consumer's preferences. In these cases, the ICDA makes its recommendations based on an underlying multi-attribute utility function of the target consumer without (necessarily) taking into account the preferences of other consumers. Statistical methods that are common to this type of ICDA include conjoint analysis, ideal point models, and regression models (including logit models), among others. Myproductadvisor.com, which operates on the basis of the individual responses to a series of questions that are designed to elicit relevant attribute preference information, is one example of this type of approach. For an offline example, we can look to the Metro Group's store of the future, which makes wine recommendations based on food selected by the shopper and its database of well-matched wine-food pairings.

Another general category of approaches to ICDA design is known as *collaborative filtering*. This technique works by comparing information about the target consumer to other consumers that are similar based on previous behavior and/or stated preference information. Recommendations can then be made by identifying products that similar consumers have purchased (or searched for) and that the target consumer has not purchased (or searched for). Amazon.com's personalized recommendations are based on such a process. In a simple collaborative filtering approach, the recommendation will be generated using a weighted sum of similar people's preferences, with similar people identified through a cluster analysis. In a more advanced form, the underlying model may use sophisticated statistical techniques (e.g., Bayesian preference models, neural networks, latent class segmentation, classification and regression trees, etc.) and include a broader set of input information (e.g., stated preferences, preferences of similar consumers, expert evaluations, attribute information, etc.; see, e.g., Ansari, Essegaier and Kohli 2000).

Goals for Agent Design

Regardless of the underlying preference architecture of the ICDA, or the role that it is playing, West et al. [1999] argued that agents should be designed with three goals in mind: 1) to improve decision quality; 2) to increase customer satisfaction; and 3) to develop trust by acting in the best interest of the consumer. Initial research results suggest that ICDAs have the potential to successfully achieve each of these objectives.

Improving Decision Quality

A traditional axiom in consumer decision making research has been that to improve decision making quality, one has to increase the amount of effort expended. However, it has been demonstrated that, with ICDA assistance, consumers are often able to increase the quality of the decisions that they make while simultaneously decreasing the effort required to make these decisions [Todd and Benbasat 1999; Diehl et al. 2003; Häubl and Trifts 2000]. For example, Häubl and Trifts [2000] conducted a large-scale experiment to examine the benefits to consumers of using an ICDA to shop for a backpacking tent and a mini stereo system in an online store.

These authors used two measures of decision quality. First, the share of consumers who chose one of six products that had been designed to be objectively superior to all other available products was 93 percent when an ICDA was available and only about 65 percent without such assistance. The second measure of decision quality was based on a switching task. After completing their shopping trips, subjects were given an opportunity to switch from their original choice in each product category to one of several attractive alternatives, all of which had already been available on the preceding shopping trip. Switching was taken as an indication of the (poor) quality of a subject's initial purchase decision. While 60 percent of the consumers who had shopped without ICDA assistance changed their choice of product, only 21 percent of those who had received ICDA assistance switched.

In addition, research suggests that the presence of personalized product recommendations enables consumers to make purchase decisions with significantly less effort than would be required otherwise. Häubl and Trifts [2000] measured consumers' search effort on a shopping trip as the number of products for which a detailed description was inspected. They found that, on average, consumers looked at the detailed descriptions of only 6.6 products when they were assisted by an ICDA, while those who shopped without such assistance inspected an average of 11.7 alternatives. This finding is consistent with the notion that reducing the effort required to make a decision is a primary motivation for using a recommendation agent, which has become widely accepted both in the field of consumer research [e.g., Alba et al. 1997; Diehl et al. 2003; Swaminathan 2003; West et al. 1999] and more generally in the literature on decision support systems [e.g., Todd and Benbasat 1999].

Increasing Consumer Satisfaction

A second goal for ICDAs that assist human shoppers is to improve consumer satisfaction. One way to do this is to create a system that is responsive to the consumer's personal preferences, and that can create or identify products that closely match these preferences [West et al. 1999]. This notion fits well with the desire of marketers to interact with customers on a one-to-one basis [Blattberg and Deighton 1991; Haeckel 1998; Peppers, Rogers and Dorf 1999]. The potential to leverage the internet, and large databases of customer information, to provide personalized products and services promises a new level of intimacy between buyers and sellers [Alba et al. 1997; Häubl, Murray and Trifts 2003; Wind and Rangaswamy 2001; West et al. 1999]. In terms of consumer satisfaction, Bechwati and Xia [2003] provided empirical evidence that interacting with an ICDA can have a positive influence. Specifically, these authors demonstrated that consumers' satisfaction with the search process is positively associated with their perception of the amount of effort that an ICDA is able to save them.

Another important component of increasing satisfaction with the buying process is limiting the monotonous or menial tasks associated with making a purchase and increasing the pleasure that consumers associate with using an ICDA. Again, the empirical evidence suggests that ICDAs are capable of improving consumers' level of enjoyment during the purchase process [Urban and Hauser 2003]. Related results indicate that ICDAs are capable of automating many aspects of decision making that consumers prefer to avoid – e.g., tasks that are tedious or otherwise unpleasant – during the process of buying or selling [e.g., Häubl and Trifts 2000; Maes et al. 1999; West et al. 1999]. In other words, a well-designed ICDA not only improves the quality of consumer decision outcomes, but it also makes the process of deciding a more pleasurable one.

Developing Trust

The ability to engender consumer trust is another important design component for ICDAs. To be effective, it is commonly believed that ICDAs should become trusted advisors [e.g., Häubl and Murray 2006; Trifts and Häubl 2003; Urban, Sultan and Qualls 2000; West et al. 1999]. Initial evidence suggests that consumers are willing to place a considerable amount of trust in an ICDA. For example, in a recent study, consumers who received product recommendations from an ICDA were twice as likely to choose the recommended product as consumers who shopped without such assistance [Senecal and Nantel 2004]. Moreover, these authors found that product recommendations by ICDAs were more influential than those provided by human experts.

Similarly, Urban and Hauser [2003] found that customers trusted a virtual advisor that assisted them in making automobile purchase decisions by an 8-to-1 margin over automobile dealers, and that they would be more likely to purchase a vehicle recommended by an ICDA by a 4-to-1 margin over one recommended by an automobile dealer. Moreover, in the same study, consumers indicated that they would be willing to pay for the advice provided by an ICDA over and above the cost of the car. As was the case with the goals of decision quality and consumer satisfaction, empirical evidence has emerged to suggest that ICDAs are capable of becoming trusted advisors.

Other Benefits of Interactive Consumer Decision Aids

In addition to demonstrating that ICDAs are capable of meeting the initial goals of improving decision quality and customer satisfaction, as well as engendering consumer trust, a number of articles have reported other benefits of such assistance. For example, it is possible for ICDAs to lead consumers to pay lower prices [Diehl et al. 2003]. In practice, an internet shopbot that searches for the lowest price for a particular product or service is a common form of ICDA.

It has also been shown that ICDAs that allow a company to “listen in” during the consumer decision making process have the potential to benefit both the firm providing the ICDA and the consumer using the ICDA. This process involves the firm recording and analyzing the conversation between the ICDA and the consumer as a purchase decision is being made. Research in this area indicates that listening in can provide companies with a substantial advantage in the product development process by improving their understanding of consumers’ preferences and identifying “new high-potential unmet-need segments” [Urban and Hauser 2003]. Similarly, it has been argued that firms should be able to substantially improve their relationships with consumers if they can use technology to become advocates for their customers [Trifts and Häubl 2003; Urban 2004] and provide products that better match customers’ preferences [e.g., Wind and Rangaswamy 2001].

Barriers to the Successful Adoption of ICDA Technology

The initial visions for a new world of buyer-seller interaction have yet to materialize. While it has been demonstrated that ICDAs are capable of providing valuable assistance to consumers in terms of improving decision quality, increasing satisfaction, developing trust, lowering price, improving product design, and reducing decision making effort (even automating portions of the process), ICDAs have not come to dominate internet shopping and they have almost no presence in the offline world. It seems that the initial consumer response to much of what ICDAs have to offer has been: "No Thanks" [Nunes and Kambil 2001]. Although somewhat surprising given the benefits of ICDAs discussed above, this finding is consistent with the more general consensus that decision support systems tend to be used far less often than anticipated by their proponents [Adelman 1992; McCauley 1991]. In addition, ICDAs have been far less effective in real-world settings than laboratory tests would have predicted [O'Connor, Rostom, Fiset, Tetroe, Entwistle, Llewellyn-Thomas, Holmes-Rovner, Barry and Jones 1999; Yates, Veinott and Patalano 2003]. As a starting point, it is likely that the successful adoption of these tools will require consumers to perceive that ICDAs offer a clear advantage relative to unassisted decision making.

One reason that ICDA adoption has not lived up to its potential may be that the criteria that a consumer uses to assess the quality of a decision are different from the criteria used by the ICDA. For instance, the ICDA and the consumer do not necessarily agree on what constitutes a good decision. In fact, research suggests that consumers define decision quality in multifaceted ways, which differ between people and within the same people at different times [Yates et al. 2003]. ICDAs, on the other hand, tend to define decision quality the same way, or in a highly constrained set of ways, for all decisions and decision makers. Therefore, while the system makes recommendations or provides information consistent with a good decision, where decision quality is defined by, say, X+Y, decision makers will sometimes use X+Y and sometimes just X, or Y+Z, or just Z. As a result, although the system is "assisting" in a manner that is consistent with the outcome it believes the consumer desires, the consumer will often be looking for a different outcome and find assistance that is inconsistent with that outcome unhelpful.

This can be especially problematic to the extent that the ICDA makes recommendations that clearly contradict the consumer's preferences. Under such circumstances, the consumer may not only reject the recommendation, but may react against the recommender. When this happens consumers are more likely to be dissatisfied with the process, and possibly the ICDA, and they are more likely to choose something different from the recommended alternative than if they had received no recommendation at all [Fitzsimons and Lehmann 2004].

Another problem, recently articulated by Simonson [2005], is that because preferences tend to be highly context dependent and constructive in nature [Bettman, Luce and Payne 1998], it is difficult to elicit reliable information that can be used to make effective recommendations. If the preference information that the ICDA bases its recommendations on is unstable and/or unreliable, the ability of the ICDA to be effective is reduced considerably.

The lack of compelling incentives – perceived or real – for consumer to use ICDA systems, and for firms to create such tools, is also a barrier to the wide-spread adoption of ICDA technologies. For consumers, there are two major issues. The first of these is *privacy.* To make intelligent individual-level recommendations, the ICDA has to know something about the consumer. This means that the tool must compile some information about the consumer by observing (and recording) behavior, and/or it must explicitly elicit information from the consumer about his or her preferences. Ignoring, for the moment, the fact that there is some doubt that the tool is able to effectively elicit preferences [Simonson 2005], it is not clear that consumers are willing to provide accurate preference information even if they could.

Of course, the ability of the ICDA to engender trust may, to some degree, alleviate this problem. However, it is likely that in any particular instantiation of an ICDA, the tool will be a "double agent" [Häubl and Murray 2006]. That is, the tool works on behalf of the consumer based on the parameters built into it by its designers [e.g., Alba et al. 1997; Lynch and Ariely 2000]. The objectives, and economic incentives, of these designers – many of whom may themselves be vendors – are not necessarily aligned with those of the consumer. To the extent that this leads to suboptimal or unsatisfactory decisions, the ICDA is likely to lose credibility and consumer trust [Fogg 2003]. If this, in turn, results in a decrease in the consumer's willingness to share personal information, then the ability of the ICDA to perform effectively will be reduced further.

The second major concern for consumers is *ease of use*. According to the Technology Acceptance Model [Davis 1989], there are two key determinants of information technology acceptance: perceived usefulness and perceived ease of use. Usefulness is defined as the extent to which a technology is viewed as being advantageous in some way. For example, a car navigation system is useful if it helps drivers find their destination and a price search engine is useful if it helps consumers find the lowest price for a product they desire. However, even if people believe that a technology will substantially improve their performance, they will still not adopt it if it is too difficult to use. In other words, if the costs of using a technology outweigh the benefits, the technology will not be accepted.

The incentives for firms can be equally controversial as many current ICDAs are, in essence, price search engines. As a result, participating by providing information to the ICDA may not be very attractive. If cooperating with an ICDA means that the firm is forced to compete primarily on price, there may be a strong incentive to avoid such cooperation. In addition, it is not clear that all products are designed to compete in a marketplace where consumers are able to efficiently and effectively match their preferences to the available products. In fact, some products may benefit from consumers' inability to accurately screen and evaluate the available alternatives.

Consumer decisions about investment and savings products are an example of this. Research suggests that most consumers struggle to understand even the most basic criteria for choosing between the different financial products that are available to them. For example, Benartzi and Thaler [2001] demonstrated that a common strategy for making investment allocation decisions is to use what they call "naïve diversification" or a "1/n" strategy. Investors using this approach divide their investments equally among the alternatives available to them – e.g., if there are ten funds available in their pension plan, 10% will be allocated to each one. Therefore, the proportion of their portfolio that is allocated to stocks depends on how many stock funds are part of the plan, rather than how much an investor should put into equities to achieve the outcome s/he desires.

Furthermore, many of the investment products that are purchased by consumers are dominated by superior alternatives. For example, the vast majority of mutual funds that are sold to consumers underperform – i.e., provide returns lower than – a corresponding index fund [Bazerman 2001; Bogle 1994]. Yet, "the mutual fund industry is among the most successful recent financial innovations. In aggregate, as of 2001, mutual funds held assets worth $11.7 trillion or 17% of our estimate of the 'primary securities' in their national markets" [Khorana, Servaes and Tufano 2005, p. 145]. According to Bazerman [1999, 2001], much of this success has been driven by the fund industry's ability to capitalize on "investor biases – including overconfidence, optimism, failure to understand regression to the mean, and vividness [2001, p. 502]." To the extent that an ICDA would eliminate, or at least reduce, such biases in consumer decision making, and lead consumers away from underperforming or dominated products, some sellers would have a disincentive to participate.

Another set of problems arises when consumers are faced with the choice of which decision aid to use. Even if consumers and firms are willing and able to effectively provide useful information to an ICDA, and individually the tools are easy to use, choosing a decision aid adds another level of complexity to the decision process. Now the consumer not only has to make a purchase decision, s/he must also decide which decision aid to use to do so. Moreover, selecting the wrong ICDA can result in poor product choices [Gershoff, Broniarczyk and West 2001].

The empirical evidence on ICDAs suggests that such tools have the potential be very advantageous to consumers in a number of ways that are generally considered to be important in the buying decision process – i.e., they have the potential to be very useful. However, they may not be useful to the extent that the human and the ICDA have different notions of what constitutes a good decision, or if the tool is unable to develop a meaningful understanding of the consumer's preferences. In addition, the tool may not be perceived as easy to use if the recommendations incite psychological reactance, or if obtaining assistance requires an additional decision of what tool to use, or if using the tool itself is more difficult than making an unassisted decision. In fact, viewed through this lens, it is clear that, although there is great potential for ICDAs, better theory and principles for design are required to make them acceptable to, and adoptable by, consumers. In the remainder of this chapter, we will briefly outline areas for new ICDA research that we believe have the potential to alleviate (or solve) many of the problems that have been identified, and in so doing substantially improve the probability that the next generation of ICDAs will be accepted by consumers.

Building Better ICDAs: Opportunities for Future Research

The accuracy and effectiveness of the assistance provided by an ICDA is directly affected by the quality of the information provided to it. For instance, if the tool's algorithm bases its recommendations on the preference information it elicits from the consumer, the quality of the advice depends critically on the quality of that input. Therefore, we suggest that the next generation of ICDAs consider incorporating a broader range of information. In this regard, it may help to elicit more than merely preference information, and to incorporate other, potentially more stable and reliable consumer inputs. For example, research has suggested that incorporating information on consumers' underlying values may lead to better recommendations and decisions [Keeney 1994]. ICDAs may also need to take a more active tutor role and teach consumers how to make good decisions [Keeney 2004; West et al. 1999]. By doing so, these tools may be able to improve the quality of the inputs they collect and, as a result, the efficacy of the assistance they provide. Whether (and how) ICDAs can fulfill this role is a potentially fruitful area for future research.

In addition, it may be helpful to design ICDAs that are capable of long-term interactions with individual consumers. Building tools that provide recommendations to millions of consumers using a single approach, and expecting all (or even most) of those people to be satisfied with the output, may be unrealistic. Instead, we suggest that creating ICDAs that learn from their experiences with a particular consumer over time, and adapt their approach based on this learning, may improve the quality of their recommendations to that individual. Initial evidence in this area indicates that different algorithms can be either more or less effective under different conditions, and that feedback is an important component of ICDA effectiveness [Ariely et al. 2004]. Nevertheless, much more research is needed that examines the potential for interactions between ICDAs and humans over extended periods of time. It would be especially interesting to better understand how long-term interaction might help alleviate some of the other problems with ICDAs identified in this chapter – e.g., input solicitation and preference discovery, incentives for consumers (privacy concerns), and minimizing psychological reactance against unsolicited or inappropriate recommendations.

It is also worth noting that our current definitions of ICDA effectiveness, including what constitutes the quality of the assistance provided, are relatively crude and could benefit from further refinement. Establishing measures of how well an ICDA is performing would go a long way towards building trust with consumers and providing an incentive for participation. As a starting point, it may be useful to consider metrics that measure consumer satisfaction, decision quality, decision efficiency, frequency of use and the importance of decisions that the ICDA is relied upon to assist the consumer with. From the firm's perspective, it would be worth knowing what consumers are willing to pay for ICDA support. In addition, sellers would be interested in financial metrics such as the return on investment of building, or providing information to, an ICDA. While the impact of search-cost-reducing technology on consumer price sensitivity has received some attention in the literature [e.g., Diehl et al. 2003; Iyer and Pazgal 2003; Lynch and Ariely 2000], the factors that affect sellers' incentives to participate in ICDAs are not well understood at this time.

A related area that can benefit significantly from additional rigorous research is the "design space" for ICDAs – i.e., what are the critical dimensions that we need to focus on when constructing effective decision support systems for consumers? For example, at what level of specificity should the understanding of consumers' preferences be represented? Is there (sufficient) value in ICDAs knowing an individual consumer's values, lifestyle, personal goals, budget constraints, etc. to justify collecting and storing such information? There are many opportunities for technology-based systems to provide assistance to consumers – e.g., the automated gathering, filtering, analysis, presentation, and storage of information about market offerings, as well as the provision of interactive decision assistance and expert advice, to name just a few. However, an important question is what the critical areas are in which consumers require and/or desire such assistance the most?

Similarly, we currently know very little about how consumers would like to interact with ICDAs. For example, to what extent should such systems act autonomously and when should they interact with consumers? The development of "interaction protocols," or an ICDA "etiquette," based on sound principles from decision research and human-computer interaction, might significantly enhance both the actual and the perceived usability of these tools. Along the same lines, there is an interesting body of research that examines the social nature of the interactions between humans and computers that has the potential to inform the design of ICDAs for long-term relationships with consumers [e.g., Moon and Nass 1996; Nass, Fogg and Moon 1996]. To the extent that consumers' interactions with ICDAs are less like market research surveys (or, worse, interrogations) and more like conversations with a friend or trusted advisor, the easier they will be to use. In turn, as the ease of use of ICDAs increases, consumers will become more likely to adopt such technologies [Davis 1989]. Most of the work in this area to date has focused on laboratory studies that require a participant to use an ICDA, which has allowed researchers to examine the consequences of human-ICDA interaction. Further research aimed at examining the decision to use (or not use) an ICDA in the first place, as well as the key determinants of consumers' ICDA choices, is clearly warranted.

More effective, successful and widely adopted ICDAs may also require a change in the approach that firms take to their relationships with consumers. Persuading consumers to buy the firm's products, whether or not they represent the best fit to their personal preferences, will be much more challenging in a world where ICDAs filter out alternatives that do not closely match a consumer's preferences. Instead, firms may have to play more of an advocate role. For example, Urban [2004] argues that in response to increasingly knowledgeable consumers, innovative companies will have to try a non-traditional approach: they will have to "provide customers with open, honest, and complete information – and then find the best products for them, even if those offerings are from competitors … if a company advocates for its customers, they will reciprocate with their trust, loyalty and purchases – either now or in the future [p. 77]. " This perspective is very consistent with the broader notion that "marketing should be less about representing the company to the customer and more about representing the customer to the company" [Sheth and Sisodia 2005, p. 161]. What we have proposed in this chapter, in terms of the design of advanced decision aids for consumers and the ensuing transformation of how firms and consumers interact with each other, is clearly an ambitious agenda. However, it is one that we believe offers a number of exciting areas for future research in marketing decision modeling.

References

Abowd, G. D., E. D. Mynatt, T. Rodden. 2002. The human experience [of ubiquitous computing]. *Pervasive Computing* **1**(1) 48-57.

Adelman, L. 1992. *Evaluating decision support and expert systems*. Wiley, New York, NY.

Adomavicius, G., A. Tuzhilin. 2005. Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE Transactions on Knowledge and Data Engineering* **17**(6), 734-749.

Alba, J., J. G. Lynch, B. Weitz, C. Janiszewski, R. Lutz, A. Sawyer, S. Wood. 1997. Interactive home shopping: Consumer, retailer, and manufacturer incentives to participate in electronic marketplaces. *Journal of Marketing* **61**(3) 38-53.

Ansari, A., S. Essegaier, R. Kohli. 2000. Internet recommendation systems. *Journal of Marketing Research* **37**(3) 363-375.

Ariely, D., J. G. Lynch, M. Aparicio. 2004. Learning by collaborative and individual-based recommendation agents. *Journal of Consumer Psychology* **14**(1&2) 81-95.

Bakos, J. Y. 1997. Reducing buyer search costs: Implications for electronic marketplaces. *Management Science* **43**(12) 1676-1692.

Baumeister, R., K. Vohs. 2003. Willpower, choice and self-control. In: G. Loewenstein, D. Read, R. Baumeister (eds.) *Time and decision*. Russell Sage Foundation, New York, NY.

Bazerman, M. H. 1999. *Smart money decisions*. Wiley, New York, NY.

Bazerman, M. H. 2001. Consumer research for consumers. *Journal of Consumer Research* **27**(4) 499-504.

Bechwati, N. N., L. Xia. 2003. Do computers sweat? The impact of perceived effort of online decision aids on consumers' satisfaction with the decision process. *Journal of Consumer Psychology* **13**(1&2) 139-148.

Benartzi, S., R. H. Thaler. 2001. Naïve diversification strategies in defined contribution saving plans. *American Economic Review* **91**(1) 79-98.

Bettman, J. R., M. F. Luce, J. W. Payne. 1998. Constructive consumer choice processes. *Journal of Consumer Research* **25**(3) 187-217.

Blattberg, R. C., J. Deighton. 1991. Interactive marketing: Exploiting the age of addressability. *Sloan Management Review* **22**(1) 5-14.

Bogle, J. C. 1994. *Bogle on mutual funds*. Irwin, New York, NY.

Borland, J. 1998. Move over megamalls, cyberspace is the great retailing equalizer. *Knight Ridder/Tribune Business News*. April 13, 1998.

Botti, S., S. S. Iyengar. 2006. The dark side of choice: When choice impairs social welfare. *Journal of Public Policy & Marketing* **25**(1) 24-38.

Brynjolfsson E., M. D. Smith. 2000. Frictionless commerce? A comparison of Internet and conventional retailers. *Management Science* **46**(4) 563-585.

Carmon, Z., K. Wertenbroch, M. Zeelenberg. 2003. Option attachment: When deliberating makes choosing feel like losing. *Journal of Consumer Research* **30**(1) 15-29.

Davis, F. D. 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly* **13**(3) 319-340.

Deci, E. L. 1975. *Intrinsic motivation*. Plenum Press, New York, NY.

Deci, E. L. 1981. *The psychology of self-determination*. Heath, Lexington, MA.

Deci, E. L., R. M. Ryan. 1985. *Intrinsic motivation and self-determination in human behavior*, Plenum Press, New York, NY.

Diehl, K., L. J. Kornish, J. G. Lynch. 2003. Smart agents: When lower search costs for quality information increase price sensitivity. *Journal of Consumer Research* **30**(1) 56-71.

Fitzsimons, G. J., D. R. Lehmann. 2004. Reactance to recommendations: When unsolicited advice yields contrary responses. *Marketing Science* **23**(1) 82-94.

Fogg, B. J. 2003. *Persuasive technology: Using computers to change what we think and do*. Morgan Kaufmann Publishers, San Francisco, CA.

Friedman, T. L. 1999. Amazon.you. *New York Times*, February 26, 1999, p. A21.

Gershoff, A. D., S. M. Broniarczyk, P. M. West. 2001. Recommendation or evaluation? Task sensitivity in information source selection. *Journal of Consumer Research* **28**(3) 418-438.

Glass, D. C., J. E. Singer. 1972a. *Stress and adaptation: Experimental studies of behavioral effects of exposure to aversive events*. Academic Press, New York, NY.

Glass, D. C., J. E. Singer. 1972b. *Urban stress*. Academic Press, New York, NY.

Greenwald, A. R., J. O. Kephart. 1999. Shopbots and pricebots. *Proceedings of the 16th International Joint Conference on Artificial Intelligence (IJCAI-99)*.

Haeckel, S. H. 1998. About the nature and future of interactive marketing. *Journal of Interactive Marketing* **12**(1) 63-71.

Häubl, G., K. B. Murray. 2006. Double agents: Assessing the role of electronic product-recommendation systems. *Sloan Management Review* **47**(3) 8-12.

Häubl, G., K. B. Murray, V. Trifts. 2003. Personalized product presentation: The influence of electronic recommendation agents on consumer choice. In: A. Rangaswamy, N. Pal (eds.) *The power of one: Gaining business value from personalization technologies*, Trafford, Victoria, BC, 144-163.

Häubl, G., V. Trifts. 2000. Consumer decision making in online shopping environments: The effects of interactive decision aids. *Marketing Science* **19**(1) 4-21.

Hoeffler, S, D. Ariely, P. West, R. Duclos. 2006. Preference exploration and learning: The role of intensiveness and extensiveness of experience. *Organizational Behavior and Human Decision Processes* **101**(2) 215-229.

Hoyer, W. D. 1984. An examination of consumer decision making for a common repeat purchase product. *Journal of Consumer Research* **11**(3) 822-829.

Iyengar, S. S., M. R. Lepper. 2000. When choice is demotivating: Can one desire too much of a good thing? *Journal of Personality and Social Psychology* **79**(6) 995-1006.

Iyer, G., A. Pazgal. 2003. Internet shopping agents: Virtual co-location and competition. *Marketing Science* **22**(1) 85-106.

Johnson, E. J., S. Bellman, G. L. Lohse. 2003. Cognitive lock-in and the power law of practice. *Journal of Marketing* **67**(2) 62-75.

Johnson, E. J., W. W. Moe, P. S. Fader, S. Bellman, G. L. Lohse. 2004. On the depth and dynamics of online search behavior. *Management Science* **50**(3) 299-308.

Kahneman, D., A. Tversky. 1984. Choices, values, and frames. *American Psychologist* **39** 341-350.

Keeney, R. L. 1994. Creativity in decision making with value-focused thinking. *Sloan Management Review* **35**(4) 33-41.

Keeney, R. L. 2004. Making better decision makers. *Decision Analysis* **1**(4) 193-204.

Khorana, A., H. Servaes, P. Tufano. 2005. Explaining the size of the mutual fund industry around the world. *Journal of Financial Economics* **78**(1) 145-185.

Langer, E. J., J. Rodin. 1976. The effects of choice and enhanced personal responsibility for the aged: A field experiment in an institutional setting. *Journal of Personality and Social Psychology* **34**(2) 191-198.

Lynch, J. G., D. Ariely. 2000. Wine online: Search costs affect competition on price, quality and distribution. *Marketing Science* **19**(1) 83-103.

Maes, P., R. H. Guttman, A. G. Moukas. 1999. Agents that buy and sell. *Communications of the ACM* **42**(3) 81-91.

Mandel, N., E. J. Johnson. 2002. When web pages influence choice: Effects of visual primes on experts and novices. *Journal of Consumer Research* **29**(2) 235-245.

McCauley, C. 1991. Selection of national science foundation graduate fellows: A case study of psychologists failing to apply what they know about decision making. *American Psychologist* **46** 1287-1291.

Mick, D. G., S. M. Broniarczyk, J. Haidt. 2004. Choose, choose, choose, choose, choose, choose, choose, choose: Emerging and prospective research on the deleterious effects of living in consumer hyperchoice. *Journal of Business Ethics* **52**(2) 207-211.

Montaner, M., B. Lopez, J. L. de la Rosa. 2003. A taxonomy of recommender agents on the Internet. *Artificial Intelligence Review* **19**(4) 285-330.

Moon, Y., C. Nass. 1996. How 'real' are computer personalities? Psychological responses to personality types in human-computer interaction. *Communication Research* **23**(6) 651-674.

Murray, K. B., R. Chandrasekhar. 2006. Home Depot Canada: Renovating strategy. Ivey Business School Case Study. Ivey Publishing, London, ON.

Murray, K. B., G. Häubl. 2007. Explaining cognitive lock-in: The role of skill-based habits of use in consumer choice. *Journal of Consumer Research* **34**(1) 77-88.

Murthi, B. P. S., S. Sarkar. 2003. The role of the management sciences in research on personalization. *Management Science* **49**(10) 1344-1362.

Nass, C., B. J. Fogg, Y. Moon. 1996. Can computers be teammates? *International Journal of Human-Computer Studies* **45**(6) 669-678.

NTT. 2006. Press release: Actual proof experiment of the autonomous operational type service robot [http://www.ntt.com].

Nunes, P. F., A. Kambil. 2001. Personalization? No thanks. *Harvard Business Review* **79**(4) 109-112.

O'Connor, A. M., A. Rostom, V. Fiset, J. Tetroe, V. Entwistle, H. Llewellyn-Thomas, M. Holmes-Rovner, M. Barry, J. Jones. 1999. Decision aids for patients facing health treatment or screening decisions: Systematic review. *British Medical Journal* **319** 731-734

Payne, J. W., J. R. Bettman, E. J. Johnson. 1993. *The adaptive decision maker*. Cambridge University Press, Cambridge, UK.

Payne, J. W., J. R. Bettman, D. A. Schkade. 1999. Measuring constructed preferences: Towards a building code. *Journal of Risk and Uncertainty* **19**(1-3) 243-270.

Peppers, D., M. Rogers, B. Dorf. 1999. Is your company ready for one-to-one marketing? *Harvard Business Review* **77**(1) 151-160.

Perlow, L. A. 1999. The time famine: Toward a sociology of work time. *Administrative Science Quarterly*, **44**(1) 57-81.

Perlow, L. A., G. A. Okhuysen, N. P. Repenning. 2002. The speed trap: Exploring the relationship between decision making and temporal context. *Academy of Management Journal* **45**(5) 931-955.

Rotter, J. B. 1966. Generalized expectancies for internal versus external locus of control of reinforcement. *Psychological Monographs* **80** 1-28.

Rust, R. T., D. V. Thompson, R. W. Hamilton. 2006. Defeating feature fatigue. *Harvard Business Review* **84(**2) 98-107.

Schulz, R., B. H. Hanusa. 1978. Long-term effects of control and predictability-enhancing interventions: Findings and ethical issues. *Journal of Personality and Social Psychology* **36**(11) 1194-1201.

Schwartz, B. 2005. *The paradox of choice: Why more is less*. Harper Collins, New York, NY.

Schwartz, B., A. Ward, J. Monterosso, S. Lyubomirsky, K. White, D. Lehman. 2002. Maximizing versus satisficing: Happiness is a matter of choice. *Journal of Personality and Social Psychology* **83**(5) 1178-1197.

Senecal, S., J. Nantel. 2004. The influence of online product recommendations on consumers' online choices. *Journal of Retailing* **80**(2) 159-169.

Sheth, J. N., R. S. Sisodia. 2005. A dangerous divergence: Marketing and society. *Journal of Public Policy & Marketing* 24(1) 160-162.

Shugan, S. M. 1980. The cost of thinking. *Journal of Consumer Research* **7**(2) 99-111.

Simon, H. A. 1955. A behavioral model of rational choice. *Quarterly Journal of Economics* **69**(1) 99-118.

Simon, H. A. 1957. *Models of man*. Wiley, New York, NY.

Simonson, I. 2005. Determinants of customers' responses to customized offers: Conceptual framework and research propositions. *Journal of Marketing* **69**(1) 32-45.

Stigler, G. J., G. S. Becker. 1977. De gustibus non est disputandum. *American Economic Review* **67**(2) 76-90.

Swaminathan, V. 2003. The impact of recommendation agents on consumer evaluation and choice: The moderating role of category risk, product complexity, and consumer knowledge. *Journal of Consumer Psychology* **13**(1&2) 93-101.

Taylor, S. E. 1989. *Positive illusions: Creative self-deception and the healthy mind*. Basic Books, New York, NY.

Taylor, S. E., J. D. Brown. 1988. Illusion and well-being: A social psychological perspective on mental health. *Psychological Bulletin* **103**(2) 193-210.

Thompson, D. V., R. W. Hamilton, R. T. Rust. 2005. Feature fatigue: When product capabilities become too much of a good thing. *Journal of Marketing Research* **42**(4) 431-442.

Todd, P., I. Benbasat. 1999. Evaluating the impact of DDS, cognitive effort, and incentives on strategy selection. *Information Systems Research* **10**(4) 356-374.

Trifts, V., G. Häubl. 2003. Information availability and consumer preference: Can online retailers benefit from providing access to competitor price information? *Journal of Consumer Psychology* **13**(1&2) 149-159.

Urban, G. L. 2004. The emerging era of customer advocacy. *Sloan Management Review* **45**(2) 77-82.

Urban, G. L., J. R. Hauser. 2003. 'Listening in' to find unmet customer needs and solutions. MIT Sloan School Working Paper No. 4276-03 [available at SSRN: http://ssrn.com/abstract=373061 or DOI: 10.2139/ssrn.373061].

Urban, G. L., F. Sultan, W. J. Qualls. 2000. Placing trust at the center of your internet strategy. *Sloan Management Review* **42**(1) 39-48.

Weiser, M. 1991. The computer for the 21st century. *Mobile Computing and Communications Review* **3**(3) 3-11.

Weiser, M. 1993. Some computer science issues in ubiquitous computing. *Communications of the ACM* **36**(7) 75-84.

West, P. M., D. Ariely, S. Bellman, E. Bradlow, J. Huber, E. J. Johnson, B. Kahn, J. Little, D. Schkade. 1999. Agents to the rescue? *Marketing Letters* **10**(3) 285-300.

Wind, J., A. Rangaswamy. 2001. Customerization: The next revolution in mass customization. *Journal of Interactive Marketing* **15**(1) 13-32.

Yates, J. F., E. S. Veinott, A. L. Patalano. 2003. Hard decisions, bad decisions: On decision quality and decision aiding. In: S. L. Schneider, J. Shanteau (eds.) *Emerging perspectives on judgment and decision research*. Cambridge University Press, Cambridge, 13-63.

Yoffie, D. B. 2005. Wal-Mart 2005. Harvard Business School Case. Harvard Business School Publishing, Boston, MA.