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Personalization without Interrogation:  
Towards more Effective Interactions between Consumers and Feature-Based Recommendation Agents

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### Abstract

Software agents that provide consumers with personalized product recommendations based on individual-level feature-based preference models have been shown to facilitate better consumption choices while dramatically reducing the effort required to make these choices. This article examines why, despite their usefulness, such tools have not yet been widely adopted in the marketplace. We argue that the primary reason for this is that the *usability* of recommendation systems has been largely neglected – both in academic research and in practice – and we outline a roadmap for future research that might lead to recommendation agents that are more readily adopted by consumers.

### Personalization without Interrogation:

#### Towards more Effective Interactions between Consumers and Feature-Based Recommendation Agents

Imagine that you are considering buying a new car. You have some general ideas about what you like and do not like, but your preferences are fairly vague and your knowledge of the marketplace is quite limited. Fortunately, you have a friend who is an automobile expert, with an exhaustive knowledge of what is for sale and a deep understanding of the consumer decision making process in this domain. You meet your friend for coffee and, after some small talk, you tell him that you are looking to buy a new car.

As you might expect, your friend begins by asking you a few questions about how you plan to use the car. However, his approach is a little unusual – he runs through a long list of potential uses and asks you to rate, on an 11-point scale, how important each one of them is to you. Nevertheless, since he is the expert, you play along. He then asks you about the price range that you are interested in. You tell him around \$30,000, but he will only accept a range of prices, and so you say \$25,000 to \$35,000. At this point, you are starting to feel a little annoyed, but you remain hopeful that this strange interrogation will lead you to the car of your dreams. Your friend then goes on to ask you about various brands, body types, interior features, engine types, and safety features – and he wants you to tell him how desirable you think each of these is, again using an 11-point scale.

In some of these categories, you are really not sure what your friend is talking about. In others, you don't have a strong preference one way or the other. He tells you to just skip any questions you do not understand or are uncomfortable with, but warns you that this could reduce the quality of the advice he will (eventually) be able to give you. So you go ahead and dutifully answer everything that he asks. Just when you think he has run out of questions, he asks you to tell him which of the long list of

car features that you have been discussing are the most important to you and which of your preferences are most deeply held. You again provide an answer, and after that he (finally) tells you which cars he is recommending to you – he presents you with his top-five list of the models that he believes would be best for you. You exchange a few pleasantries and head home to decide which car to buy. At this point, you probably feel confused, maybe a little frustrated, and quite certain that the process you just went through is not something that you want to go through again anytime soon.

Yet, this is precisely the type of approach used by many of today's "best" feature-based product recommendation tools for consumers. (Although, while your friend at least talked to you, most of these tools would require you to type your answers). In this article, we argue that the knowledge and technology exist to allow us to build better recommendation agents (RAs) and facilitate more effective interaction between consumers and such agents than what is evident in current practice. We begin with a brief review of prior research suggesting that RAs have the potential to substantially improve consumer decision making. We then argue that the *usefulness* of recommendation systems will not be recognized by consumers until these tools become more natural and *easy to use*.

Drawing on recent research in consumer behavior and human-computer interaction, we suggest that more emphasis needs to be placed on making these tools accessible and usable – not just to improve RA adoption, but to also make such tools commercially viable. We sketch out a roadmap for future research in this area and comment on the theoretical and practical implications of improving our understanding of consumer-agent interaction.

#### Personalized Recommendations Based on Individual-Level Feature-Based Preference Models

In this article, we focus on RAs that construct a preference model for an individual consumer, and then use that model as a basis for making personalized product recommendations to that consumer (see, e.g., Alba, Lynch, Weitz, Janiszewski, Lutz, Sawyer, & Wood, 1997; Häubl & Trifts, 2000; West,

Ariely, Bellman, Bradlow, Huber, Johnson, Kahn, Little, & Schkade, 1999). The discussion that follows applies specifically to those RAs that engage a consumer in an *explicit* dialogue about their preferences for different features of the products and then builds a profile of that single consumer's preferences, which is then used to filter the products available in the marketplace and sort those products based on the individual's specific profile.

We focus on this particular type of recommendation agent, because we believe that there is a substantial, yet currently untapped, potential for these tools to assist consumers in their decision making (Diehl, Kornish, & Lynch, 2003; Häubl & Trifts, 2000; Senecal & Nantel, 2004; Urban & Hauser, 2004). Researchers have been making considerable progress in terms of how to best model the behavior and preferences of individual consumers as a basis for generating personalized recommendations (e.g., Adomavicius & Tuzhilin 2005; Bodapati, 2008; De Bruyn, Liechty, Huizingh, & Lilien, 2005; Montgomery, Hosanagar, Krishnan, & Clay, 2004; Toubia, Simester, Hauser, & Dahan, 2003). Yet, the current (almost negligible) market share of such tools appears to be inconsistent with their relative efficacy (e.g., Ariely, Lynch, & Aparicio, 2004). Given the significant potential of emerging modeling techniques (e.g., De Bruyn et al., 2005; Toubia et al., 2003) and our increasingly deep understanding of how consumers respond to RAs (Bo & Benbasat 2007; Cooke, Sujan, Sujan, & Weitz, 2002; Diehl, Kornish, & Lynch, 2003; Häubl & Trifts, 2000; Kramer, 2007; Murray & Häubl, 2008; Swaminathan, 2003), tools of this type represent a profound opportunity to dramatically improve consumer decision making in the near future.

In choosing to focus on this particular class of RA, we are intentionally leaving some well-known examples of personalization out of our analysis. In fact, there are a number of currently active personalization technologies that are capable of providing reasonably good recommendations without "interrogating" consumers. Amazon.com provides customers with recommendations based on an ever evolving algorithm that incorporates past purchases with the preferences of other similar consumers

(i.e., collaborative filtering), as well as direct responses from users, to produce individualized shopping advice. Netflix.com is currently running a competition to improve its own approach to movie recommendations, which employs a variety of techniques designed to more effectively match available rentals to people's preferences. Pandora.com has become a favorite among music aficionados and casual fans alike for its ability to provide streaming audio that is tailored to individual tastes based on the user's ratings of previously played tunes. Similarly, human recommendations can have an important impact on the buying process. In fact, user-generated content of a variety of types is a popular source of shopping advice – this could include anything from product reviews to testimonials on ecommerce sites, as well as peer-to-peer information disseminated through online social networks.

Why then have we chosen to focus on the relatively less popular and successful type of RA that builds a profile based on an explicit dialogue with the consumer? We have adopted this approach precisely because it is becoming less relevant than other technologies, yet in many ways it has the potential to add significantly to the overall efficacy of consumer recommendations. Prior research has demonstrated that such RAs can be extremely effectively when consumers take the time to learn how to use them, and when these tools have the opportunity to learn about the individual consumer (Diehl, Kornish, & Lynch, 2003; Häubl & Trifts, 2000; Senecal & Nantel, 2004; Urban & Hauser, 2004). Although a review of the literature on the benefits of such RAs is beyond the scope of the current work, it worth noting that this style of RA has important benefits beyond what tools based on other approaches are capable of offering. For example, Ariely, Lynch, and Aparicio (2004) found that individual-level feature-based RAs are more adaptable to changes in consumer preferences and, as a result, tend to perform better than other approaches over the long-term.

It may be that such tools will evolve to be an important subset of recommendation systems. More likely, profiling consumers based on a session of explicit questions and answers will, ultimately, be combined with other approaches (e.g., collaborative filters, pattern recognition, user-generated

content, etc.) to develop the most effective recommendations. In any case, we believe that by making individual-level feature-based RAs more attractive to consumers our ability to effectively assist consumer decision making will be greatly enhanced. Therefore, even though other approaches to personalization have so far been more readily adopted, it is worth continuing to work on improving the question and answer approach that we are focusing on here. However, we also believe that people are unlikely to adopt such RAs if it means subjecting oneself to an interrogation, even in return for better recommendations. The central thesis of this article is that improving the ease with which consumers can overtly explicate their preferences to a machine will open the door to the large-scale adoption of such tools.

#### Decision Assistance in an Increasingly Complex World

Many purchase decisions require consumers to make a tradeoff between the accuracy or quality of the decision and the effort invested in making it (Payne, Bettman, & Johnson, 1993). For example, when buying a new book, a comprehensive search of all retailers selling that book is likely to result in a lower price than simply returning to ones' favorite store. However, each visit to another store looking for a better price takes effort. As a result, consumers tend to satisfice (Simon 1955) – they make a purchase as soon as they find a product that meets some basic criteria, even if additional searching might reveal a better alternative and/or a lower price. To the extent that effort is costly, this is a very reasonable approach.

Interestingly, many consumers appear to be reluctant to search even when the cost of visiting one more retailer is quite low. For example, 70% of internet shoppers have been found to be loyal to just one online bookstore (Johnson, Moe, Fader, Bellman, & Lohse, 2004). These consumers tend to simply return to the same vendor from which they made their most recent book purchase, and tend not to visit other internet stores that are only “a click away.” This is true even though, on average, prices for

the same book can differ substantially between vendors and the most popular internet bookstores – i.e., the ones with the largest market shares – are typically not the ones that offer the lowest prices (Brynjolfsson & Smith, 2000).

When consumers are willing to engage in a more extensive search, the variety of products for sale and the number of choices that have to be made can be overwhelming. There is a cost to thinking that increases as decisions become more complex (Shugan, 1980) and, clearly, consumption decisions are becoming more complex. Whether deciding what show to watch on TV (or the internet), what type of car to buy, where to invest our savings, even what type of cracker we want to eat – American grocery stores commonly carry more than 85 varieties (Schwartz 2004) – today's consumer faces a number of complex choices on a daily basis. Given our limited capacity to process information and the finite amount of time we have to make such decisions, it is not surprising that people tend to continue doing what has worked well for them in the past (Hoyer, 1984; Stigler & Becker, 1977).

Even so, recent research has indicated that having too much choice can lead to negative consequences that extend beyond increased demands on consumers to process information. Examples of such effects include increased regret, decreased product and life satisfaction, lower self-esteem, and less self-control (e.g., Baumeister & Vohs, 2003; Botti & Iyengar, 2006; Carmon, Wertenbroch, & Zeelenberg, 2003; Schwartz, Ward, Monterosso, Lyubomirsky, White, & Lehman, 2002). Related research has shown that, although consumers may prefer to buy products that have more features and capabilities, their ultimate satisfaction with their purchases decreases to the extent that these very features make products more difficult to use (Thompson, Hamilton, & Rust, 2005). These findings are not just important for buyers; this type of decrease in consumer satisfaction tends to also have a negative impact on sellers' long-term profitability (Rust, Thompson, & Hamilton, 2006).



## The Promise and Potential of Recommendation Agents

Recommendation agents are a promising solution to the problems of too much information and too much choice for consumers (Murray & Häubl 2008). Indeed, it has been shown that the use of such tools tends to increase the quality of consumers' consumption choices while reducing the amount of effort required to reach these decisions (Häubl & Trifts, 2000). Moreover, by making it easier for shoppers to obtain information about product quality, RAs can increase consumer price sensitivity and, as a result, enable consumers to pay lower prices (Diehl et al., 2003). Initial evidence also indicates that RAs are often viewed as credible and trustworthy advisors (Komiak & Benbasat, 2006; Senecal & Nantel, 2004; Urban & Hauser, 2004).

Yet, these individual-level RAs that have proven to be so effective in the laboratory are exceedingly rare in the real world. Consumers have balked at the idea of this type of personalization and, in many cases, simply say "No Thanks" (Nunes & Kambil, 2001). However, such RAs *have* seen at least a limited amount of success in cases where they act as "double agents" that are promoted as tools designed to help consumers make better decisions, but that are created and funded by sellers who have a vested interest in influencing consumers' choices (Häubl and Murray 2003, 2006).

## Taking Advice from a Machine

Prior research has shown that consumers who use RAs can benefit by making better consumption decisions (including paying lower prices) with less effort, and that those who have used different types of individual-level RAs tend to find them to be credible advisors. In other words, RAs are trusted advisors that substantially improve consumer decision making. Why, then, have consumers been so slow to adopt these tools? We suggest that one of the major barriers to adoption is not the *usefulness* of RAs; instead, it is how *usable* they are. Take, for example, the car recommender at MyProductAdvisor.com, which is regarded as one of the best available third-party RAs. After consumers

answer a long list of questions about their automobile preferences, the tool provides a sorted list of recommended vehicles. Unfortunately, answering many of the questions requires a fairly high level of automobile expertise, which means that this tool will be most effective for those who already know a great deal about cars and their own preferences within that domain.

Consumers' need for advice and decision assistance is typically negatively correlated with their expertise in a given product category – that is, the more we know about a domain, the less we need advice from an external source (e.g., Godek & Murray 2008; Yaniv, 2004; Yaniv & Kleinberger, 2000). Similarly, with the possible exception of the most highly motivated consumers, when looking for a product recommendation, most people tend to prefer something that provides them with answers quickly. They are also likely to prefer an interaction that is natural and comfortable – and we would argue that very few consumers find expressing their preferences via a large number of rating scales natural and comfortable. Research clearly indicates that, as the perceived usability of technology decreases, the probability that it will be adopted also decreases (Davis 1989).

It is also worth recognizing that RAs are not the only source of recommendations. The consumer decision making process often involves asking others for advice or information. Whether that person is a friend, a salesperson, an acknowledged expert, or simply a conveniently available informant (e.g., a taxi driver), people tend to talk to others routinely, and often informally, about the consumption choices they are about to make. To be widely useful, RAs must provide some value over and above what these other sources offer. Clearly, the evidence in the literature suggests that RAs have some advantages – e.g., enormous information processing capabilities, virtually unlimited memory, enabling better decisions with less effort, powerful search engines, highly trusted, etc. – over other types of advisors. Yet, in other ways, this type of RA technology lacks some of the key characteristics of the advisors that consumers tend to consult. As discussed above, the format in which RAs elicit preference information is likely to be unnatural and uncomfortable for many consumers. In addition, RAs have very

little knowledge of the context within which the consumer is requesting a recommendation. They also lack “soft” skills – i.e., emotional or social intelligence. And, importantly, consumers are creatures of habit who face a cognitive cost in switching away from what they know to a new source of product and service recommendations. In what follows, we discuss each of these weaknesses of current RA technologies and suggest that they can be overcome once researchers begin to put as much emphasis on the usability of RAs as we have devoted to examining their usefulness.

### Habitual Consumption and the Adoption of Recommendation Systems

As consumers learn to achieve their goals, they establish routines of habitual behaviors that can be difficult to modify. For example, many people routinely return to the same grocery store for their regular food purchases. Similarly, online shoppers tend to return to the same website to buy books, CDs, travel arrangements, and other products (Johnson, Bellman, & Lohse, 2003). This is the case even though such consumption routines tend to sacrifice an optimal decision (i.e., lower prices, better selection of products, etc.) that could be achieved through a broader search in exchange for expending less effort (Stigler and Becker 1977). By returning to the same seller over and over again, people are able to become more efficient buyers. In previous work, we have demonstrated that people who develop habitual patterns of consumption over repeated experiences become very resistant to switching (Murray & Häubl, 2007). In particular, when people learn to satisfy a consumption goal with one set of behaviors, they tend to carry out those same behaviors each time the goal is activated. When this behavior becomes habitual – i.e., it is performed automatically, with little or no conscious awareness and without consideration of alternatives – consumers become locked-in.

When it comes to obtaining recommendations about products that we are interested in purchasing, most consumers have patterns of behavior that became deeply entrenched at an early age – that is, we ask another person for advice. Receiving advice from a machine is a very new phenomenon,

and it is one that competes with well-established behavioral routines. As a result, choosing to solicit a recommendation from an RA requires the consumer to modify their existing pattern of behavior. The difficulty inherent in modifying deeply ingrained behavioral routines can be reduced if the new activity is relatively easy to engage in (Murray and Häubl, 2007). However, in their current form, individual-level RAs do not appear to be easy to use; especially when they are evaluated relative to advice from a human.

Another complicating factor in the adoption of new tools or systems (e.g., pieces of software) is what has been referred to as the “*paradox of the active user*” – the persistent tendency for users of a new software system to focus on achieving their current, short-term goal with the system as opposed to taking time to learn how to use the system properly, which would benefit them in the longer term (Carroll & Rosson, 1987). That is, when it comes to software, people do not like to learn and then use; they prefer to use immediately and learn what they need to as they go. However, jumping right into using a new system renders people susceptible to missing out on learning its novel functions – which may well be its most useful ones – especially if these functions require significant new user skills. Therefore, in order to better understand consumer adoption of RA technologies, it is important to examine these systems from a user-skills perspective and, in particular, to consider the extent to which consumers’ pre-existing skills overlap with those required by an RA.

If consumers are to change their current patterns of behavior (i.e., how they solicit product recommendations), they must be given a new way to accomplish their goal(s) (i.e., getting recommendations)(Murray and Häubl, 2007; Wood, Quinn, & Kashy, 2002). Given enough time to experience and become familiar with an RA, the cost of use would likely decrease and the benefits would become more salient. However, it has been shown that consumers are hesitant to invest today in exchange for future benefits (Zauberman 2003). That is, consumers tend to prefer to pay a higher ongoing cost (e.g., lower decision quality and more effort), rather than incur a substantial set-up cost

(i.e., learn to use the RA properly) that will result in lower ongoing costs (e.g., higher decision quality and less effort). For RAs, this means that lowering the initial effort required to use these tools is important, if they are going to be more widely adopted.

### *Making it Easy*

Fortunately, preliminary work has demonstrated that consumers are quite willing to switch to a new alternative when the latter is very similar to what they have been using (Murray and Häubl 2002). In a laboratory experiment, we examined the responses of two groups of consumers to the introduction of a new online product screening tool. Both groups were asked to use an incumbent RA to complete a series of 6 shopping tasks. During these tasks, participants learned to use the tool progressively more efficiently to the point where they had cut their initial task completion times in half after six trials. We then asked all participants to use a new product screening tool that appeared to be either (1) different from, or (2) very similar to, the incumbent. We found that those in the “similar” condition exhibited a preference for the new tool and, when asked to choose one of the two tools to complete additional shopping tasks, they tended to prefer the new interface that they had only a single experience with. Those who were in the “different” condition preferred the incumbent interface and were reluctant to switch.

Further analysis suggested that whether or not consumers were willing to adopt the new interface was driven by the extent to which they felt that they were able to transfer the way they were shopping with the incumbent to the competitor. When they could transfer those behaviors, the new alternative was attractive. When they had to learn new behaviors, they tended to stick with what they already knew (Murray and Häubl 2002). Subsequent studies confirmed this initial finding and demonstrated that habits of use can be a powerful determinant of consumer choice (Murray and Häubl 2007). Although this research offers encouraging preliminary evidence, it is important to note that it

examined switching from one computer-based tool to another, and that prior use of the incumbent was fairly limited. Convincing people to switch from relying on human advisors to soliciting and accepting recommendations from machines is likely to be more challenging.

### *The Perceived Value of Personalization*

One apparent solution to the need for an RA to be easy to use upon adoption is to build personalized recommendation systems – i.e., to personalize not only the recommendations provided to the consumer (which is what RAs do), but also the interface that the consumer uses to interact with the RA. If the RA interface is personalized to the specific usage patterns and preferences of a consumer, it will be easier to use than if it operates in the same general way for all users. However, this might not be as straightforward as it sounds. First, it is very difficult to personalize an RA interface for a consumer *before* the consumer has used the RA. Yet, this is necessary if the RA is going to be easy to use on the very first trial, which prior research suggests is critical to increasing the probability that it will be used again (Carroll & Rosson, 1987; Murray & Häubl, 2007; Zauberger, 2003). Second, even if it was possible to provide some personalization the first time a consumer used the RA, it may not be enough to convince people to change their consumption habits. In a recent study, we found that the value added by personalization is not immediately apparent to consumers and that it requires multiple uses of a personalized website for people to recognize the benefits they are receiving relative to a standard interface (Murray, Häubl, & Johnson, 2008). This suggests that, although personalization is one potential solution to the problem of ease of use that is worthy of additional investigation, designers should also continue to look for other ways to improve the initial ease of use of such tools.

### More Efficient Agent Algorithms

Research in marketing has recognized the problems inherent with a traditional approach to preference elicitation that requires answers to a long list of questions before a profile can be generated and recommendations made. In response, over the past couple of decades, some very innovative algorithms have been developed to gain a deep understanding of a consumer with a minimum of queries. An early, and popular, example of such an approach is Sawtooth Software's Adaptive Conjoint Analysis (ACA) (Johnson 1987). This program allowed for an interactive questionnaire that customized stimulus presentation to individual respondents based on their answers to previous questions. The ability to adapt the design of questions within – as opposed to across – respondents, is an important feature of approaches that aim to develop preference models at the individual level, with a minimum number of questions. More recently, the algorithms underlying adaptive questionnaires have been improved and incorporated into available software (e.g., Toubia et al., 2003). In addition, new approaches are being developed that further reduce the number of questions that need to be asked and improve the speed with which recommendations can be made. In one noteworthy example, De Bruyn and colleagues developed a stepwise componential regression approach that asks an average of only *two* questions, yet it was shown to be more accurate than a full-profile conjoint study that asked an average of *twenty-one* questions (De Bruyn et al., 2005). If an RA can make an accurate recommendation after asking only a couple of questions, this makes it much more comparable, in terms of communication efficiency, to what consumers are used to when they solicit recommendations from other humans.

In addition to minimizing the number of questions that need to be asked, RAs may also benefit from longer-term interactions with consumers that allow them to improve the individual-level preference model and, potentially, the relationship between the human and the agent. For the most part, current RA systems are designed to provide “one-off” recommendations – i.e., they do not

incorporate data about previous interactions with the consumer, nor do they anticipate future interactions. However, initial evidence indicates that RAs that generate recommendations from individual-level preference models can benefit greatly from feedback over repeated trials (Ariely et al., 2004). In addition, recent work in human-computer interaction has demonstrated that incorporating “social intelligence” (see *Anthropomorphic Agents* below) into an agent can substantially increase the respectability, likability, and trustworthiness of a tool, as well as consumers’ preference for it in the long term (Bickmore & Picard, 2005). Although work examining human-agent interactions over extended periods of time is still in its early stages, the preliminary evidence suggest that this area has the potential to substantially improve the success and acceptance of machine-based recommendations.

### Anthropomorphic Agents

Although better recommendations based on fewer questions would represent a substantial improvement over current RA technologies, such advances would only partly address the issue of easing the transition from human recommendations to taking advice from a machine. Another important piece of the puzzle is likely to be the development of interfaces that exhibit affective responses and social intelligence (Picard 1997). There is strong evidence to suggest that people treat computers like they treat humans – that is, we respond to computers as social actors in much the same way that we respond to other people (Burgoon, Bonito, Bengtsson, Cederberg, Lundeberg, & Allspach, 2000; Reeves & Nass, 1996; Sundar, 2004).

However, so far, the architects of recommendation agents have failed to incorporate this fact into their designs; instead, their focus has been on the development of better database systems and algorithms – i.e., on usefulness. We suggest that this is an important oversight, and that designing RAs that respond and interact more like humans than machines has the potential to greatly improve the attractiveness and, consequently, the adoption of these tools.



Consumers are unlikely to return for recommendations to a friend who ignores the context of a request for advice, asks a long list of questions before providing a response, and demonstrates a complete lack of personality and social intelligence. Why then would we expect people to make use of RAs that treat them in this way? Given that people respond to computers much like they do other humans, it is not surprising that consumers have reacted negatively to RAs that behave like interrogators. Moreover, because people are more likely to switch to a new way of doing things when they can transfer many of their current behaviors and skills to the novel situation, the more RAs can act like people, the easier it will be for consumers to adopt them.

#### *Recommendation Agents as Social Actors*

While people may anthropomorphize some inanimate objects, we of course do not treat every machine as if it were human. According to Nass and Moon (2000), people tend to treat technology as if it were human when it outputs information as words (Turkle, 1984), is interactive in the sense that it bases its responses on multiple prior inputs (Rafaeli, 1990), and serves in a role that has been traditionally performed by humans (Cooley, 1966; Mead, 1934). Clearly, RAs fit these criteria.

Given that people are likely to treat computerized RAs as they would other people, effectiveness may be highly correlated with “affectiveness.” We are not advocating the development of the emotional androids of science fiction; however, even the addition of a few of the rudimentary conventions of human-to-human interactions can go a long way. For example, Tzeng (2004) demonstrated that when computers apologized for errors, users’ preference for the machine increased and they reported that they enjoyed the experience more. Consumers also seem to prefer recommendations that come from computers that appear to be working hard on their behalf (Bechwati & Xia, 2003).

One current approach to making computers more anthropomorphic is to introduce avatars – i.e., human (or humanoid) characters that change expressions and whose appearance can be customized by users. Avatars have been introduced on a broad variety of websites from Yahoo’s email program to online poker sites (e.g., FullTiltPoker.com) to search engines (MsDewey.com) and internet clothing retailers (e.g., The Gap and Land’s End) (Hemp, 2006). Recent research has shown that the use of avatars in online shopping environments tends to have a favorable impact on consumers’ attitudes towards retailers and their merchandise (Holzwarth, Janiszewski, & Neumann, 2006). If RAs begin to adopt similar techniques, they may also be able to improve their interactions with consumers by better matching characteristics such as the gender and/or ethnicity of an avatar to the individual user (Nass & Moon, 2000).

Similarly, research indicates that people prefer computer-based agents that display empathy – i.e., show concern for the human user’s welfare. For example, in an experiment using a computerized blackjack game, Brave, Nass, and Hutchinson (2005) manipulated empathy by changing the expression of the dealer (i.e., a picture of a human face that was identified as the dealer) and the text message that the dealer displayed to the player. In the empathetic condition, the dealer smiled when the player won and looked disappointed when the player lost, as opposed to displaying a neutral expression in the non-empathetic condition. In addition, the empathetic dealer expressed emotion in the text message (relative to the non-empathetic condition) – e.g., by saying “I am sorry that you lost” versus “The dealer beat you” or “You won! That’s wonderful!” versus “You won this time.” The results indicate that the empathetic dealer was better liked, believed to be more trustworthy, and perceived to be more supportive than its non-empathetic counterpart.

Taking empathy a step further, researchers have developed programs that monitor users’ physiological activity (e.g., through skin conductance and electromyography) and use that information to provide affective feedback through an avatar (Prendinger, Dohi, Wang, Mayer, & Ishizuka, 2004) –

e.g., the program apologizes to a user that becomes frustrated as a result of a slow response from the computer or congratulates a user who has achieved a desirable outcome.

Clearly, research examining computers with personality and empathetic avatars is still at an early stage this point. However, work in this field continues to evolve as the systems become more adept at recognizing and responding to users' emotions. Moreover, the initial evidence is consistent in demonstrating that when computers incorporate elements of typical human social interaction into their algorithms, they are able exert greater influence on human decision making than do their "cold" counterparts (Picard 1997; Reeves & Nass 1996). It is worth noting, however, that these effects do not occur because people think that computers are humans; instead, the evidence indicates that people *mindlessly* apply the same social rules to computers that are relied upon in human-to-human interactions (Nass & Moon 2000). Enhancing our understanding of how these rules are applied when consumers solicit and receive advice, and incorporating this knowledge into the design of future RAs, could go a long way towards improving the ease with which people are able to use recommendation systems.

#### Ambient Intelligence and Multi-Agent Systems

In addition to the increased usefulness that can be achieved through better algorithms and the greater ease of use that may be possible with socially intelligent RAs, recommendation systems are also likely to benefit from designs that are explicitly aware of the context within which they provide advice. The concept of ambient intelligence builds on the notion of ubiquitous computing (Weiser 1991, 1993) and principles of human-centric computer design to develop multi-agent systems that take advantage of information about the user's current situational context and geographic location. While a review of the large and growing literature in this area is well beyond the scope of the current article, interested

readers are referred to Remagino, Foresti, and Ellis (2004) and Weber, Rabaey, and Aarts (2005) for an in-depth discussion of the concept of ambient intelligence.

The potential of these types of systems can be illustrated with a brief example of an RA that specializes in restaurant recommendations. Using GPS information, local maps, time of day, as well as knowledge of the user's food preferences and access to his or her calendar, our (imaginary) restaurant recommender can be loaded as a software application onto a mobile phone. When the consumer requests a restaurant recommendation, the RA can take into account not only what type of food s/he likes (a basic requirement for this type of RA), but also the consumer's current location (GPS information), what restaurants are nearby (map information), and how much time the consumer has (based on calendar information). Moreover, if the RA has access to other, related agents (i.e., if it is part of a multi-agent recommendation system), it may also be capable of conducting queries beyond its own database to incorporate other information such as weather (is sitting on the patio a good idea?), restaurant ratings (both professional and those of other consumers), average wait times, nutritional information, and so on. If the RA has the ability and permission to act autonomously, it may also reserve a table and even contact some of the consumers' friends with an invitation to lunch.

This example may sound somewhat farfetched; however, rudimentary versions of this type of RA are currently in operation. For example, Acura's in-car navigation system responds to a verbal request from the driver for restaurant recommendations. It uses Zagat's Restaurant Ratings and the car's current location to map out all of the options that meet the consumer's criteria (e.g., requesting "Chinese Food" will map the location of all Chinese Food restaurants that are within a specified distance from the current location, including ratings, where applicable). Carnegie Mellon's MyCampus project involves a more advanced version of a multi-agent system that can personalize recommendations in a variety of domains from a handheld PDA (Sadeh, Chan, & Van, 2002; Sadeh, Gandon, & Kwon, 2005). The advantage of incorporating more context-specific information into recommendations is obvious –

without having to ask the consumer additional questions, the RA is able to provide a highly personalized response that is not only consumer-specific, but also situation-specific. As a result, incorporating ambient intelligence into the future generations of RAs has the potential to improve both the tool's ease of use and its usefulness.

### Conclusion

In this article, we have attempted to shed some light on the reasons why, despite their apparent usefulness, software agents that provide consumers with personalized product recommendations based on individual-level preference models have not yet been widely adopted in the marketplace. Our key argument is that consumer demand for such recommendation agents has been low largely because of their poor *usability*. That is, we contend that the creators of recommendation systems have focused primarily on enhancing the usefulness of these tools to consumers (e.g., the breadth and depth of market coverage, the accuracy of preference models, etc.), while devoting insufficient effort to making them easier to use. Moreover, this is mirrored by the emerging body of academic research on consumer behavior in connection with recommendation agents, which to date has also largely neglected issues of usability.

We have focused on those factors that might suppress consumer demand for recommendations based on individual-level preference models. We believe that the most significant barriers to the market success of recommendation agents have been on the demand side, and that making it easier for consumers to use these systems (along the lines suggested in this article) is the key to their large-scale adoption. However, it is important to recognize that supply-side factors may also have contributed to the lack of wide-spread adoption of model-based tools for personalized recommendations in the marketplace. In particular, issues such as the economic incentives both for the providers of

recommendations systems and for the sellers who participate by making their product assortments “recommendable” deserve rigorous examination.

Nevertheless, given that humans tend to treat computers like people, it is reasonable to suspect that computers – and, in particular, recommendation systems – would be more attractive to consumers if they acted like people. For example, RAs have historically asked far more questions than a human advisor would before providing a recommendation. In addition, prior research has demonstrated that people prefer to interact with anthropomorphic computer systems – for example, software agents that incorporate human gestures and appearances and interact with users in a polite and empathetic manner. Technologies such as natural language and ambient intelligence may also be important in this regard.

Finally, it is important to recognize that, even if future RAs are capable of greater social intelligence, they will still face a substantial barrier in modifying consumers’ current advice-taking habits and routines. Although there is evidence to suggest that usability will help in this regard (Murray and Häubl 2007), there is still a great deal that we do not yet understand about the interaction between consumers and electronic recommendation agents. We believe that the low current rate of adoption of RAs that explicitly ask questions to build individual consumer profiles and make recommendations, should not discourage scholars from continuing to investigate and improve our understanding of such approaches. This is an emerging area of research that is likely to continue to grow as the interface between firms and their customers becomes increasingly computer-mediated. Importantly, the results and discoveries that arise from this line of research should be of great interest to marketing theory and practice, as well as to a number of other fields ranging from information systems and computing science to economics and psychology.

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