Interaction Design for Mobile Product Recommendation Agents: Supporting Users' Decisions in Retail Stores

YOUNG EUN LEE
Fordham University
and
IZAK BENBASAT
University of British Columbia

Mobile product recommendation agents (RAs) are software systems that operate on mobile handheld devices, using wireless Internet to support users' decisions en route, such as consumers' product choices in retail stores. As the demand for ubiquitous access to the web grows, potential benefits of mobile RAs have been recognized, albeit with little supporting empirical evidence. We investigate whether and how mobile RAs enhance users' decisions in retail stores by reducing the effort to make purchase decisions while augmenting the accuracy of the decisions. In addition, to identify potential design principles for mobile RAs, we compare and evaluate two interaction styles of mobile RAs: alternative-driven (RA-AL) versus attribute-driven (RA-AT) interactions. The results of a laboratory experiment conducted in a simulated store indicate that mobile RAs reduced users' perceived effort and increased accuracy of their decisions. Furthermore, RA-AL users made more accurate decisions than RA-AT users due to the RA-AL's interaction style, which was compatible with the way in which users processed information and made decisions in the store. These empirical results support the notion that mobile RAs should be designed to fit the user's task undertaken in the particular context.

Categories and Subject Descriptors: H.1.2 [**Models and Principles**]: Human information processing—*User/Machine Systems*; H.5.2 [**Information Interfaces and Presentation**]: Interaction styles—*User Interfaces, Evaluation/methodology*

General Terms: Design, Experimentation, Human Factors

1. INTRODUCTION

Product recommendation agents (RAs) are Web-based software systems that advise consumers about what to buy based on the needs expressed by those consumers [Xiao and Benbasat 2007]. Many online retailers have employed RAs to resolve the information overload consumers experience on the web [Riedl and Dourish 2005]. Recently, a new type of RAs has emerged, namely, mobile RAs that operate on portable handheld devices, such as cellular phones or personal digital assistants (PDA), through wireless networks [Van der Heijden 2006]. Using mobile RAs for in-store decision making has become widespread as a result of three trends: (1) increased computing power of portable handheld devices, (2) popularity of these handheld devices among the general public, and (3) advances in wireless technologies that provide information about products [Van der Heijden 2006]. In one survey, 90% of mobile RA users said that they found recommendations from a wireless device useful [Miller et al. 2003].

Mobile RAs are designed to provide immediate support to consumers choosing a product in a store filled with a number of alternatives and distractions [Joshi 2000; Miller et al. 2003; O'Hara and Perry 2001]. In retail stores, consumers often are exposed to point-of-purchase promotional messages, displayed products, and additional information presented on price tags [Youll et al. 2001]; often in inconsistent formats [Russo 1977]. Consequently, consumers struggle to collect, integrate, and comprehend such information [Russo et al. 1986], acquiring inaccurate and/or biased information in the process that leads them to make suboptimal product choices [Wansink et al. 1998]. In this light, the primary role of mobile RAs is to reduce the complexity of purchase choices that consumers face in retail stores, thereby helping them reach the best decision possible while reducing the effort needed to make the decisions.

Mobile RAs also provide support to consumers who make partially planned purchases in stores, including (1) generally planned purchases where consumers had the product category in mind, without a particular brand or product, and (2) substitute purchases where consumers changed from the specifically planned items to others [Abratt and Goodey 1990]. A survey published in 1993 showed that partially planned purchases as well as impulse purchases accounted for 30% (conservative) to 50% of total retail purchases [Phillips and Bradshaw 1993]. The significant portion has not decreased despite the widespread availability of information technologies that enable planned, informed decisions [Lo et al. 2010; Miller 2009]. Indeed, 60% of the time, shoppers make brand decisions after entering the store [Miller 2009]. More-over, a decrease in planned purchases has been reported as today's consumers

make very hurried decisions due to work stress and the lack of leisure time [Lo et al. 2010].

Simultaneously, information provided at the point of purchase instigates consumers to make substitute purchases [Youll et al. 2001]. Many unexpected factors that exist in retail stores, such as others' recommendations, special discounts, and unavailability of the preselected item, alter consumers' choices [Youll et al. 2001]. For these reasons, a shopper who has a particular product in mind before going to a store often purchases another product in the end. Mobile RAs can serve as beneficial tools, providing reviews of products and resources for comparison shopping, thereby reducing consumers' post-purchase regrets and complaints [Lo et al. 2010]. However, despite such promises, only a handful of studies have empirically examined the benefits of mobile RAs for consumers' in-store decision making, for example, Van der Heijden [2006] and Kowatsch and Maass [2010]. Therefore, we aim to investigate whether and how mobile RAs assist consumers' purchase choices in physical retail stores, compared to RA nonuse.

In addition, we attempt to find optimal mobile RA interaction styles that augment consumers' in-store decision making. It is necessary to find an interaction style designed specifically for in-store purchases as effective designs for stationary RAs cannot be transferred blindly to mobile RAs [Lee and Benbasat 2003]. Mobile users' goals, tasks, and needs differ from stationary users because they use mobile applications situated in a dynamic context that involves their own movement (e.g., walking) and spontaneous needs to react and process the cues in their physical surroundings [Dix et al. 2000; Lee and Benbasat 2003]. Consumer behavior literature indicates that consumers' in-store decision-making processes differ from those of consumers not physically located in stores for one significant reason: in-store consumers are exposed to product alternatives displayed on the store shelves. As visual stimuli attract people's attention most saliently [Suh and Lee 2005], consumers naturally are led to inspect the products displayed [Underhill 1999]. While inspecting products on shelves, they see whole products (e.g., a Nikon digital camera) and then analyze individual attributes of the products (e.g., the shutter, zoom lens, price of the camera) [Biehal and Chakravarti 1982]. In contrast, consumers, in the absence of physical products, first recall the goals of their purchase (e.g., what do I want from a digital camera?) and the attributes to achieve the goals (e.g., red-eye removal) before thinking about the whole product [Lynch Jr and Srull 1982]. In other words, in-store consumers process information in an alternative-driven manner (initiated by a product alternative, followed by analyses of its attributes) whereas consumers without access to product displays process information in an attribute-driven manner (initiated by product attributes, followed by analyses of the product that contains these attributes). As a result, we argue that mobile RAs should be designed in an alternative-driven manner (RA-AL) as opposed to an attribute-driven manner (RA-AT) as RA-AL fits in-store consumers' information-processing pattern better. The fit between the interaction style afforded by software applications and users' tasks further enhances user performance [Kunde 2003; McLaughlin

et al. 2009]. Therefore, mobile RAs that provide an alternative-driven interaction style should improve in-store decision performance.

This claim is contrary to the widely accepted tenet in multialternative/multiattribute decision-making literature that an attribute-based decision-making approach is more intuitive and easier to use [Payne et al. 1993; Russo and Dosher 1983]. Consistent with the tenet, prior studies on stationary RAs have found that consumers, in the absence of physical products, were more satisfied with the decision-making processes, learned more, and perceived less complexity in the choice set when provided with decision aids employing attribute-based approaches rather than alternative-based approaches[1] [Huffman and Kahn 1998; Kamis et al. 2008]. By empirically showing that RA-AT and RA-AL users' performances are reversed for in-store shopping, we demonstrate the importance of designing interactions specifically for mobile applications instead of blindly applying interaction styles developed for stationary RAs.

In summary, this study has two goals: (1) compare mobile RA use for in-store shopping to RA nonuse and (2) compare RA-AL to RA-AT in terms of users' decision performance. To achieve the two goals, we conducted a laboratory experiment in an artificial store. The experiment employed a 1×3 full factorial design with three levels of RA conditions: nonRA (control), RA-AL, and RA-AT.

The remainder of this article is organized as follows. Section 2 presents a summary of previous research upon which our hypotheses on the difference between RA use and RA nonuse as well as RA-AL and RA-AT are derived. Section 3 presents the research method utilized to test the hypotheses. Section 4 presents data analyses and their results, and Section 5 concludes with a discussion of the findings and their implications for theory and practice.

2. THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

2.1 Summary of Previous Research

Numerous studies have investigated stationary RAs' roles for Web-based shopping, identifying factors such as RA use, RA features (equivalent to interaction styles in this study), user characteristics, and decision problems (such as decision tasks and context) as antecedents of users' decision making and/or their intentions to accept RAs [Brown and Jones 1998; Eierman et al. 1995; Xiao and Benbasat 2007]. Among these, the research question that received the most attention is whether and how RA use reduces user effort in making decisions and increases the accuracy of those decisions. In contrast, the effect of decision

[1]These prior studies did not use the term *RA*, but instead used *decision support systems* [Kamis et al. 2008] or *information presentation format* [Huffman and Kahn 1998]. However, these are similar to RAs in the sense that both elicit consumers' preferences for a product and help them choose one from a number of products. In addition, we note that the terms used in the prior studies, that is, alternative- and attribute-*based* processing, are similar to our terms, that is, alternative- and attribute-*driven* interaction styles. See section 2.3, *Interaction Designs of RA-AL and RA-AT*, for more detailed descriptions of the commonalities and differences between alternative-/attribute-*based* processing and alternative/attribute-*driven* approaches.

context on users' decision making has received the least attention, despite its increasing importance. The prior research that examined these two research questions are presented below.

RA use reduces users' efforts in reviewing products [Haubl and Trifts 2000 and Haubl and Murray 2005]. RA use also increases decision accuracy: RA users have reported higher objective decision accuracy [Diehl 2005; Haubl and Trifts 2000; Swaminathan 2002] and higher subjective confidence in their decisions [Haubl and Trifts 2000; Swaminathan 2002]. Many of these studies are based upon the literature on multialternative/multiattribute decision making that involves selecting one from a number of alternatives described by a common set of attributes [Svenson 1979]. To solve multialternative/multiattribute choice problems, individuals apply various decision strategies [Payne et al. 1993]; many RAs are built based upon these strategies [Song et al. 2007]. Decision strategies are distinguished in terms of various dimensions, some of which are compensatory (i.e., a poor value of one alternative's attribute can be compensated by a favorable value of another attribute) while others are noncompensatory (i.e., a poor value of one alternative's attribute results in a premature elimination of the alternative) [Payne et al. 1993]. Because noncompensatory strategies allow decision makers to eliminate alternatives based upon certain threshold levels, they require less effort while simultaneously resulting in less accurate decisions. The use of compensatory strategies, in contrast, leads to more accurate decisions, although they require more effort to thoroughly review all the alternatives and attributes [Payne et al. 1993].

Second, decision strategies differ in terms of the direction of information processing, including alternative-based and attribute-based processing [Payne et al. 1993]. In alternative-based processing, all the attributes of an alternative are reviewed holistically. In contrast, in attribute-based processing, based on an individual attribute, the values of several alternatives are processed. According to Russo and Dosher [1983], attribute-based processing is cognitively easier. Consistent with this conclusion, two studies on stationary decision aids, Huffman and Kahn [1998] and Kamis et al. [2008], have revealed that decision aids employing attribute-based processing are preferred to those employing alternative-based processing. This is because the attribute-based processing is easier to use and allows users to explore various options for customization [Huffman and Kahn 1998; Kamis et al. 2008]. However, we underscore that these studies concern stationary decision aids, not mobile decision aids (e.g., RAs), and were not conducted in an in-store context. Because consumers process information in a very distinct way when they are in a store displaying real products [Bettman and Zins 1979; Russo and Leclerc 1994], it is questionable whether the superiority of RAs employing attribute-based processing over alternative-based processing holds for in-store decision making.

In addition, as noted earlier, effects of decision context have been largely neglected in the RA literature [Brown and Jones 1998; Eierman et al. 1995; Xiao and Benbasat 2007]. Context is an external setting in which users make decisions [Eierman et al. 1995]. Consumer psychology literature has demonstrated the substantial impact of context effects on users' decision making

[Slovic 1995]. However, the studied effects of context are limited to the similarities of alternatives, the attractiveness of the alternative set, and reference point effects [Payne et al. 1993]. With regard to the lack of research on context effects, Eierman et al. [1995], page 5, asserted that, "[a] theory of DSSs would not be complete without considering the environment in which a DSS is developed, implemented and used."

Very few studies have included the in-store decision-making context in their investigation of the effectiveness of mobile RAs. To the best of our knowledge, only two empirical studies have investigated how mobile RAs assist consumers' decision making in retail stores: Kowatsch and Maass [2010] and Van der Heijden [2006]. Van der Heijden [2006] developed a mobile RA that provides product attractiveness cues to indicate how well the product satisfies the user's pre-specified preferences for the product category. They compared this to a mobile RA without the attractive cues in terms of the quality of users' consideration sets. The results showed that the attractiveness cue significantly increased the number of superior products in the consideration set, indicating an increase in the quality of decisions. However, their RAs were not fully interactive: the mobile RA lacked an interactive feature and thus required a research assistant to enter users' preferences for products using a desktop computer connected to the server on which the mobile RA was stored. Without a fully implemented preference-elicitation method, users cannot enter or modify their preferences freely; consequently, researchers cannot fully examine the effectiveness of the mobile RA. In addition, Kowatsch and Maass [2010] investigated the factors that influence users' acceptance of mobile RAs in an artificial store. They found that perceived usefulness and ease of use increase users' intentions to adopt mobile RAs, visit the retail store that provided the mobile RA, and finally purchase the product recommended by the RA. However, they did not investigate whether the use of mobile RAs influences users' decision-making effort or the accuracy of their in-store purchases.

In summary, no empirical study to date has investigated whether and how the use of mobile RAs (fully functional and interactive RAs) reduces efforts to make decisions in retail stores while increasing accuracy. Moreover, no empirical study to date has compared the effectiveness of the two directions of information processing (alternative vs. attribute) for in-store decision making in which consumers process information in a very distinct way than consumers not in a physical store.

2.2 Research Questions

The goal of our research is to compare (1) the use of a mobile recommendation agent (RA) with nonuse, for the RA conditions of (2) alternative-driven (RA-AL) with attribute-drive (RA-AT) in terms of users' in-store decision performance. Decision performance will be measured by (1) the effort users spend to make decisions and (2) the accuracy of those decisions. In the subsequent sections, we first introduce RA-AL and RA-AT, followed by the hypotheses for comparing mobile RA use to nonuse, and finally, the hypotheses for comparing RA-AL to RA-AT.

Introduction Page	Product-List Page	Detailed-Information-About-Product Page
Information-about-Attribute Page	Comparison Page	Recommendation Page (“More Like This” Page)

Fig. 1. Screenshots of RA-AL.

2.3 Interaction Designs of RA-AL and RA-AT

RA-AL and RA-AT adopt two very contrasting ways to interact with users. The direction of interactions that lead choice processes in a sequence from product alternatives to product attributes is called “alternative-driven” (RA-AL). In contrast, the sequence from attributes to alternatives is called “attribute-driven” (RA-AT). We explain how the two interaction styles are implemented in detail later.

RA-AL prompts users to provide information about product alternatives, elicits their preferences for alternatives, and then provides recommendations based on those preferences for alternatives (see Figure 1). RA-AL first presents a list of alternatives (product-list page in Figure 1) from which users can

select products of interests and view details of the chosen products (detailed-information-about-product page). While doing this, users can also review attribute details, such as definitions and range of attributes (information-about-attribute page in Figure 1). After reviewing details of products, users select products that are worthy of further investigation for comparison (comparison page in Figure 1). Using this comparison feature, users can keep one product alternative that they find superior in the pair by removing the inferior one. The next product among those kept for comparisons is then appended to the product deemed superior in the previous comparison. Users continue to compare the chosen products until they identify one or more products that appear most appropriate for their needs. At this point, users have an option to request that the RA-AL identify six products similar to their favored ones to verify that they indeed are choosing the best alternative available.[2] Once RA-AL recommends products similar to the favored ones (recommendation page), users can compare their favored products and the RA-AL's recommendations until they reach their final choice. Examples of RA-AL can be found at www.bestbuy.com.

In contrast, RA-AT prompts consumers to acquire information about product attributes, elicits their preferences for attributes, and then provides recommendations based on those attribute preferences (see Figure 2). Specifically, RA-AT provides a list of product attributes (attribute-list page in Figure 2), from which users can review details of the attributes (information-about-attribute page in Figure 2). RA-AT then asks users to specify their preferences for these attributes and indicate the importance of the chosen preferences (preference-specification page in Figure 2). RA-AT requires users to indicate first their preferred attribute levels and then the importance of these attributes for their purchases as (1) extremely important, (2) important, or (3) somewhat important. If users choose extremely important,[3] any alternatives that do not meet the specified level are eliminated. When users choose lower importance levels, such as important and somewhat important, RA-AT multiplies the predefined standard score of an importance level by the gap between the user's chosen level and the attribute level of each alternative to calculate the overall gap score for each alternative. This procedure is repeated for the attributes that users consider being important for their purchases. The RA-AT then recommends the six products (or fewer if the user chooses to eliminate many products) that have the lowest gap scores (recommendation page). The user can also view details of the recommended products (detailed-information-about-product

[2]RA-AL and RA-AT recommend six products because consumers usually leave two to five products in their consideration set that they evaluate further to reach a choice. Both RAs could have recommended five products to provide the number of products that consumers would normally consider; however, the handheld device chosen for this study, a PDA, like most other handheld devices, allowed for the presentation of two products on one page. Thus, both RAs recommend six products, an even number that is one greater than the largest number (i.e., five) of products that comprise a consideration set to fully utilize the display space of the device.

[3]During the experiment, participants were made fully aware that the choice of "extremely important" would result in the elimination of alternatives that did not meet the chosen level whereas the choice of "important/somewhat important" would not.

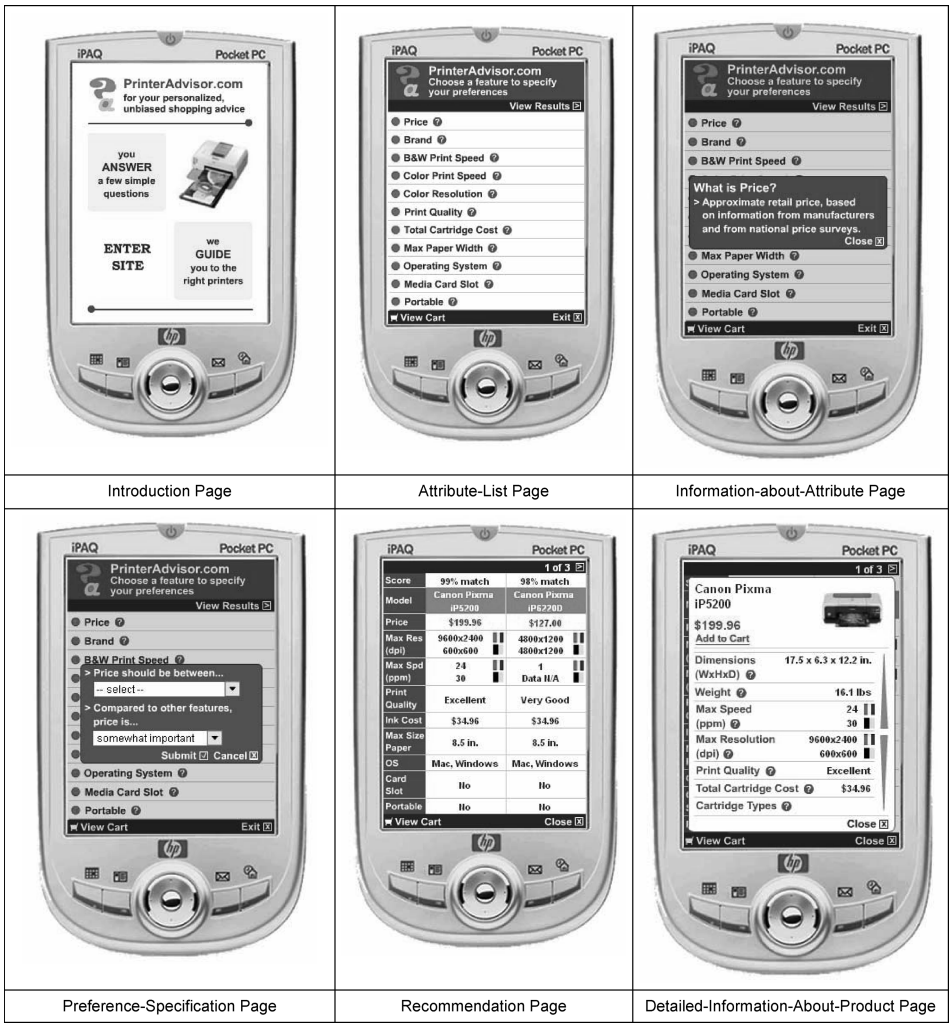

Fig. 2. Screenshots of RA-AT.

page). Examples of this type of RA can be found at www.ActiveBuyers.com and www.myProductAdvisor.com.[4]

[4]Alternative-/attribute-*driven* styles (as proposed in this study) are similar to alternative-/attribute-*based* processing [Payne et al. 1993] in the sense that the alternative-driven style prompts users' information processing in a holistic manner (i.e., alternative-based processing) and the attribute-driven style decomposes it into processing of individual attributes (i.e., attribute-based processing). The alternative-/attribute-driven styles provide recommendations and support for users to choose one of the recommended products (on recommendation pages in Figures 1 and 2), in addition to the support provided by the alternative-/attribute-based processing. Such difference is unavoidable and reflects the reality of RAs because RAs, by definition, are designed to provide recommendations and thus need to assist to users in choosing one out of the recommended products.

2.4 Hypotheses: RA Use vs. RA Nonuse

2.4.1 *Interaction Designs of RA-AL and RA-AT.* Prior studies have argued that RAs take over the effortful process of screening and sorting products based on consumers' expressed preferences so that consumers can reduce their information search and focus on alternatives that best match their preferences [Xiao and Benbasat 2007]. However, it is not as evident whether or not mobile RAs reduce consumers' effort in making decisions in stores as using RAs requires additional mental and physical effort, including entering preferences into RAs to get recommendations [Olson and Widing 2002].

Furthermore, constraints of mobile devices exacerbate the effort of entering preferences into mobile RAs. The limited and small interfaces, referred to as the "baby-face" of mobile devices [Marcus 2001], increase users' response time significantly [Albers and Kim 2000]. Such an increase is magnified when device constraints are combined with users' physical movement [Lee and Benbasat 2003]. Entering preferences into a small device is cumbersome for most users, but doing so while walking in a retail store crowded with other shoppers and sales representatives is even more effortful. Consequently, the use of mobile RAs increases the objective amount of effort to make decisions due to the constraints of mobile devices combined with users' movement; thus, mobile RA users will spend more time making decisions than RA nonusers.

H1a. RA-AL users will spend more time making decisions than RA nonusers.

H1b. RA-AT users will spend more time making decisions than RA nonusers.

However, the increase in the objective amount of effort is not directly translated into an increase in subjective effort that users would perceive [Hoffman and Novak 1996]. Although they spend more time, users feel less stressed when they are actively involved in decision-making processes [Hoffman and Novak 1996]. Using dynamic and responsive computerized systems, one becomes immersed in the interactive experience, reaching the status of "flow" where one forgets the time that passes [Hoffman and Novak 1996], (i.e., "Time flies when you're having fun"). Mobile RA users are likely to be more involved in the decision-making process because they enjoy the interactive decision-making processes supported by mobile RAs. Mobile RA users' active involvement in decision tasks will make them underestimate the time spent.

In addition, users can delegate stressful decision tasks to mobile RAs [Komiak and Benbasat 2006]. Overloaded with the excessive information in the store, RA nonusers make decisions entirely on their own, whereas mobile RA users can delegate their decisions to the RAs [Komiak and Benbasat 2006]. Because they can share the workload with mobile RAs, they can reduce the stress and anxiety, thereby finding the decision task less effortful. Consequently, we posit that, despite the increased objective amount of effort, mobile RA users will perceive less effort in making decisions than RA nonusers.

H2a. RA-AL users will perceive less effort in making product choice decisions than RA nonusers.

H2b. RA-AT users will perceive less effort in making product choice decisions than RA nonusers.

2.4.2 *Decision Accuracy.* RAs increase accuracy of consumers' purchase decisions by providing enhanced search and comparison features [Xiao and Benbasat 2007]. Certain types of RAs help users compare products in-depth before making a final decision [Haubl and Trifts 2000]. Using the comparison features, one can identify and reject suboptimal alternatives, ultimately choosing the best alternative. Search and comparison features also enhance in-store decisions by transforming "available" information into "processable" information [Russo 1977]. In a retail store without RAs, product information is provided in a much less systematic way, usually via product tags (i.e., the tags that show product price and provide brief product information) attached to the display shelves. Information about certain attributes frequently shown on one product's tag may be missing on another. Such an inconsistent presentation of information makes it extremely difficult for consumers to collect, integrate, and comprehend information about different products [Russo et al. 1986]. Thus, even if information about all product attributes is "available," consumers often fail to utilize that information unless it becomes "processable" [Russo et al. 1986].

Mobile RAs' search and comparison features make product information both available and processable, enabling consumers to utilize the information more readily and, consequently, make more accurate decisions.

H3a. RA-AL users will make more accurate product choice decisions than RA nonusers.

H3b. RA-AT users will make more accurate product choice decisions than RA nonusers.

2.5 Hypotheses: RA-AL vs. RA-AT

Prior to comparing RA-AL and RA-AT, we first illustrate the unique patterns in which consumers process information and make decisions in retail stores. Based upon the consumers' information-processing pattern, we build our assertions on differences between RA-AL and RA-AT in terms of user decision processes and outcomes.

2.5.1 *Consumers' Information Processing in Retail Stores.* According to the consumer behavior literature, consumers process information in stores very differently from homes or offices. At their homes or offices, without physical products to examine, consumers tend to recall the most important goals of their purchase (e.g., easy manipulation) and the attributes needed to achieve the goals (e.g., one-touch shutter) [Lynch Jr and Srull 1982]. Therefore, consumers process information attribute-wise [Lynch Jr and Srull 1982]. In contrast, in-store consumers are exposed to real products displayed on shelves [Underhill 1999], naturally drawing them to inspect products displayed on store shelves and acquire information from them [Russo and Leclerc 1994]. Because products are displayed on store shelves as a whole, not as parts or attributes, consumers

in the store acquire information holistically (i.e., processing by alternative) rather than decomposing them into attributes [Bettman and Zins 1979]. For instance, consumers see a whole digital camera (e.g., Cannon 1234) on the shelf rather than a zoom lens, a shutter button, a flash light, etc. Therefore, in-store consumers process information holistically or by alternative [Biehal and Chakravarti 1982; Johnson and Russo 1978].[5]

This pattern of alternative-oriented processing becomes stronger among consumers who are not familiar with the product category [Biehal and Chakravarti 1982; Huffman and Kahn 1998]. Nonexpert consumers tend to review the range of product options to familiarize themselves with the product category [Brucks 1985] whereas expert consumers can focus on those products that satisfy their preferred attribute levels [Huffman and Kahn 1998]. These less informed consumers comprise the majority of RA users, as consumers who already have firmly established knowledge in the product category do not need help from RAs [Haubl and Trifts 2000; Swaminathan 2002].

2.5.2 *Fit between Users' Information Processing and RA Interactions.* Because in-store consumers search and process information alternative-wise, we claim that RA-AL fits better with consumers' in-store information-processing pattern than RA-AT. Prior studies on stationary RAs, on the contrary, have found that attribute-based decision aids outperform alternative-based decision aids for web-based shopping, as mentioned in Section 2.1 [Huffman and Kahn 1998; Kamis et al. 2008].

Many prior studies have asserted that the fit between decision aids and users' tasks augments the users' task performance [Goodhue 2006]. The basic premise of these studies is that when the complexity in the task environment is reduced, more effective problem solving results because humans are limited information processors [Vessey 1994]. Moreover, complexity in the task environment is effectively reduced when the tools support the processes required to perform the task [Vessey 2006; Vessey and Galletta 1991]. According to Vessey [2006], a user formulates a mental representation of the given task using the characteristics of both the tool's information presentation format and the task requirements. If the information presentation format and task requirements emphasize the same type of information, a consistent mental representation is formulated and a cognitive fit occurs, subsequently leading to faster and more accurate decision making [Hong et al. 2004]. When a mismatch occurs between information format and task, a user must transform a mental representation

[5]Some may argue that products could be displayed on store shelves sorted systematically by attribute. However, it is not possible for a retail store to display complex goods on shelves sorted by each and every attribute. Complex durable goods, such as computers, have a number of common attributes (e.g., graphics, sound cards, CPU, RAM, ROM, HDD), some of which conflict. In addition, some attributes of complex products are distinct and, hence, not common to all products (e.g., fingerprint recognition specifically provided for business-use laptops). Second, retailers and manufacturers choose not to sort products by certain attributes; instead, they display products on shelves in such a way to maximize their profits. For instance, retailers display the products that offer the highest sales margins in the center section of shelves [Suarez 2005]. In addition, manufacturers buy display shelves to maximize visual attention and minimize comparison with major competitors' products [Desmet and Renaudin 1998].

to either an information-presentation format or the task, which requires additional effort and ultimately results in lower accuracy [Huang et al. 2006]. Many previous studies on the effect of web interface designs have relied on the theory of cognitive fit to explain users' superior performance [Hong et al. 2004; Huang et al. 2006; Kamis et al. 2008; Suh and Lee 2005].

2.5.3 *Indicators of Fit.* Because RA-AL's alternative-driven approach fits better with consumers' in-store information-processing patterns, RA-AL users will be able to inspect products displayed on the store shelves instantly and effortlessly as compared to RA-AT users, especially in the early stages of decision making. In-store consumers make product choices in the following sequence [Russo and Leclerc 1994]: Upon entering the store, a consumer scans products displayed on shelves briefly and sequentially, familiarizing herself with the available products, number of products, and physical layout of the store. Next, the consumer selects products worth further consideration, building a "consideration set," while eliminating others, and then compares the products in the consideration set to reach a final choice. Finally, the consumer verifies her choice by inspecting other products both in and outside the consideration set, determining the final choice. Among these, it is important to examine how mobile RAs assist consumers in the phase of screening products as consumers choose one from the consideration set established in the screening phase; thus, the effectiveness of screening products leads directly to the accuracy of the final choices [Russo and Leclerc 1994].

During the screening phase, RA-AL users can directly and quickly retrieve information about the products they find interesting on the shelf by choosing the products from a list of alternatives (product-list page in Figure 1). In other words, RA-AL users can easily acquire information from store shelves while simultaneously referring to RA-AL. In contrast, RA-AT users must first specify their preferences for attributes to initiate their choice processes; such initiation by attribute requires users to decompose products into attributes. While perusing products displayed on the shelves, a user may want to acquire information about a particular product displayed on the shelf. The goal at this point is to quickly and effortlessly obtain information about that product in order to decide whether to keep the product for further consideration or eliminate it. However, RA-AT requires the consumer to indicate preferences for general product features prior to obtaining information about the product. In other words, RA-AT's interaction style driven by attributes is mismatched with the way in which users obtain information from product displays on shelves, thereby hindering users from acquiring the information.

Consequently, one can expect RA-AT users to be less inclined to inspect on-shelf products due to the misfit in the screening phase; whereas RA-AL users can search products by freely referring to both product displays and the RA. Therefore, we posit:

> H4. RA-AL users, as compared to RA-AT users, will acquire information from products displayed on shelves while simultaneously reviewing products on the RA during the phase of screening products.

A decision aid that fits the task being undertaken achieves a cognitive fit, hence resulting in effective control of decision-making processes [Vessey 2006]. Perceived control refers to the extent to which a user controls the execution of his/her decision strategies [Sengupta and Te'eni 1993]. Perceived control increases when users feel that they can utilize the system to resolve their problem; that is, users feel that they can use a system freely and in an unrestricted way when the system enables them to solve the problems at hand [Frese et al. 1987; Morris and Marshall 2004]. On the other hand, when users perceive that the system prevents them from reaching a solution, they feel less in control because the system impedes the resolution of their problem [Frese et al. 1987]. As previously noted, RA-AL users search for and acquire product information freely in the store whereas RA-AT users are confined by the attribute-driven interactions inconsistent with their natural pattern of in-store information processing. Thus, we posit:

H5. RA-AL users will perceive higher control over the decision-making processes than RA-AT users.

2.5.4 *Comparisons of RA-AL and RA-AT in Decision Effort and Accuracy.* As previously argued, RA-AL fits the natural pattern of user information processing in retail stores; thus, the task complexity RA-AL users experience will be less than that for RA-AT users [Slovic et al. 1990]. Because task complexity is decreased, RA-AL will be able to expedite consumers' in-store decision-making processes. Consequently:

H6. RA-AL users will spend less time making decisions than RA-AT users.

We noted earlier that RA-AL users utilize product information available on store shelves during the screening phase. As a result, RA-AL users have a better chance of learning about the available range of alternatives. Knowledge of the available alternatives and their attributes enables consumers to construct more reasonable and realistic preferences for the product. To make better decisions, consumers must adapt their preferences to the reality of purchase situations [Wansink et al. 1998], taking into account negative associations among product attributes, such as affordability vis-à-vis advanced features [Haubl and Murray 2003]. These negative associations among product attributes compel consumers to compromise some of their important goals in order to achieve others [Bettman et al. 1998]. Consequently, it is important for consumers to maintain reasonable and realistic expectations of product attributes. However, because RA-AT users screen products without reviewing products available on shelves, RA-AT users have fewer chances to recognize the range of available alternatives sold in the store to adjust their expectations.

In addition, RA-AT users, when asked to choose one from all possible attribute values, will become aware of the highest attribute level, producing unreasonably high expectations for their purchases [Haubl and Murray 2003]. Recall that RA-AT provides users with a list of available attribute levels. For example, a consumer is presented with three levels of camera resolution: 1–3 megapixels, 3–5 megapixels, and 5 or more megapixels. After reviewing these

Table I. Printer Attributes

Attributes	Levels
Brand	Canon, Epson, Hewlett Packard, Kodak, Lexmark, and Samsung
Black and white print speed (in PPM [Page Per Minute])	(1) 14 ppm or lower (down to 7 ppm), (2) 15 ppm to 24 ppm, (3) 25 ppm or higher (up to 27 ppm)
Colour print speed (in PPM [Page Per Minute])	(1) 14 ppm or lower (down to 1 ppm), (2) 15 ppm to 24 ppm, (3) 25 ppm or higher (up to 33 ppm)
Colour resolution (in DPI [Dot Per Inch])	(1) 300 × 300 dpi, (2) 4880 × 1200 dpi, (3) 5760 × 1440 dpi, (4) 9600 × 2400 dpi
Print quality	(1) Fair, (2) Good, (3) Very good, (4) Excellent
Total cartridge costs (in Canadian dollars)	(1) $ 81 or more (up to $ 90), (2) $ 51 – $ 80, (3) $ 21 – $ 50, (4) $ 20 or less (down to $ 18)
Maximum printable paper width	(1) 4 inches, (2) 8.5 inches, (3) 13 inches
Operating systems	(1) Mac OS, (2) Windows
Media card support	(1) No, (2) Yes
Portability	(1) No, (2) Yes
Price (in Canadian dollars)	(1) $ 301 or more (up to $ 400), (2) $ 201 to 300, (3) $ 101 to 200, (4) $ 100 or less (down to $ 39)

levels, the consumer may anchor on the highest level (e.g., 5 or more megapixels) as a benchmark for his/her choice [Wansink et al. 1998] despite having a very limited budget. Such unreasonable expectations and the choice of less reasonable attribute levels lower decision accuracy substantially [Bettman et al. 1998; Wansink et al. 1998]. Consequently, we posit:

> H7. RA-AL users will make more accurate product choice decisions than RA-AT users.

3. RESEARCH METHOD

We conducted a laboratory experiment to test the stated hypotheses empirically. A 3 × 1 factorial design was used, with one between-subject factor of three levels: nonRA group, RA-AT group, and RA-AL group.

3.1 Alternatives and Attributes

We chose printers as the focus product for this experiment for several reasons. First, the student participants would be interested in and want to purchase printers for their school work; second, printers are complex goods with a large number of alternatives and attributes. Consumers seek help from RAs only for complex products, not for simple ones, because it is difficult to process information about complex products without RA's assistance [Van der Heijden and Sorensen 2002]. The 22 different printer models chosen for the experiment covered almost all printers sold at the time the experiment was conducted. Table I shows the 11 printer attributes chosen from the lists of common attributes mentioned in technology review websites (www.consumerreports.org, www.znet.com, and www.cnet.com) and online storefronts (www.staples.ca and www.bestbuy.ca). The ranges and levels of each attribute were drawn from real products. For participants not familiar with the attributes, the RAs

provided a link that opened a pop-up window describing each attribute in detail (detailed-information-about-product-attribute pages in Figures 1 and 2).

3.2 Computing Devices

The RAs were operated on PDAs, specifically the HP iPAQ Pocket PC h1940. This device runs on the Pocket PC 2003 operating system and has a 240 × 320 pixel resolution colour touch screen. Participants used a stylus to enter input on the PDAs. The PDAs were connected through a built-in Wi-Fi card to a campus-wide wireless Internet connection, built using the wireless Ethernet standard Wi-Fi IEEE 802.11b. Because the experiments were conducted during the university's summer break, any possible problems associated with a busy wireless network (e.g., interference and instability) were negligible.

3.3 Operationalization of the Dependent Variables

Five dependent variables were measured: (1) time spent (H1a, H1b, H6), (2) perceived effort (H2a, H2b), (3) accuracy of decisions (H3a, H3b, and H7), (4) whether or not users inspect products on shelves in the screening phase (H4), and (5) perceived control (H5).

First, we measured the time participants spent to reach purchase decisions. Perceived effort is conceptualized based upon Bechwati and Xia's [2003] four effort scales: the degree to which the use of RA required time and effort, as well as the ease and complexity of RA use.

We measured decision accuracy by counting the number of times that "desirable" products were chosen as final choices. Many previous studies measured the share of chosen products that were "nondominated" products (i.e., products that are not objectively inferior to any other alternative) by manipulating the attribute levels of all alternatives so that some products were better than others in each and every attribute. However, because we employed real products, hence, preserving ecological validity, we could not artificially manipulate attribute levels of product alternatives. Consequently, we were not able to find a single product that satisfied every consumer's total needs. However, many light and beginner printer users are likely to prefer a base model that is inexpensive and has basic levels of all attributes, whereas many expert printer-users may prefer higher-end models with higher performance in particular attributes [Swaminathan 2002]. Therefore, in the set of printers (see Table II) we included two that best satisfied the particular needs of the two segments of consumers: (1) HP Photosmart 8050 for light and beginner users and (2) Canon Pixma iP5200 for heavy and experienced expert users. (We fully justify the selection of these two printers in section 3.5). In the experiment, we provided participants with descriptions of two types of people (see section 3.4) and asked them to choose a printer for each. Then, as an indicator of decision accuracy, we measured the frequency with which these two printers (i.e., "desirable" products) were selected.

We determined whether or not participants inspected products on shelves during the screening phase by analyzing their shopping behaviours. We filmed the participants' experimental sessions. Of the 25 RA-AL and 25 RA-AT users,

Table II. 22 Printers Available

	Portable	Media Card Slot	Max Paper Width	Max Color Print Speed	Max Color Resolution	Max B&W Print Speed	Print Quality	Cartridge Cost	Sum of Attribute Levels	Price (in Canadian dollars)
HP Deskjet 9800*	1	1	3	2	2	3	3	2	17	399.95
Canon Pixma iP6600D	1	2	2	2	4	2	2	1	16	269.92
Epson Picture Mate	2	2	1	1	3	0	2	3	14	249.93
Epson Stylus Photo R340	1	2	2	2	3	2	2	1	15	249.92
HP Photosmart 8250	1	2	2	3	2	3	2	2	17	249.92
HP OfficeJet Pro K550	1	1	2	3	2	3	2	2	16	229.95
Canon Pixma iP5200	1	1	2	2	4	3	4	3	20	199.96
Canon Selphy DS810	1	2	1	1	2	0	1	4	12	179.92
Canon Pixma iP4200	1	1	2	2	4	3	1	1	15	149.36
HP DeskJet 6940	1	1	2	3	2	3	2	1	15	144.86
Canon Selphy CP510	2	1	1	1	1	0	2	4	12	129.96
HP DeskJet 5940	1	1	2	2	2	3	2	2	15	129.42
Canon Pixma iP6220D	1	1	2	1	2	0	3	3	13	127.00
HP Photosmart 8050	1	2	2	3	2	2	3	3	18	125.46
Lexmark P315	1	2	1	1	2	0	3	3	13	99.93
Epson Stylus C88	1	1	2	1	3	2	1	1	12	99.92
HP Photosmart 335	2	2	1	1	2	0	3	3	14	99.92
Canon Pixma iP6210D	1	1	2	1	2	0	3	3	13	97
HP DeskJet 5440	1	1	2	1	2	1	3	3	14	89.91
Canon Pixma iP1600	1	1	2	2	2	2	2	2	14	79.73
Samsung SPP 2020 Photo Printer	2	1	1	1	1	0	3	3	12	69.98
Lexmark Z517	1	1	2	1	2	1	1	1	12	39.98

2 RA-AL users' and 5 RA-AT users' sessions were not captured due to equipment failures. The captured experimental sessions were analyzed by two coders who were told to identify whether participants referred to both the RA and product displays at the same time during the phase of screening products. Cohen's Kappa (used to test the reliability of the multiple coder analyses) was 0.71, exceeding the acceptable reliability level suggested by Cohen [Cohen 1960] of 0.70.

Perceived control is a subjective measure determined using seven-point semantic scales developed by Bechwati and Xia [2003]. The measure was revised to fit the purpose of this study and included three control scales: control felt while specifying preferences for printers (two items) as well as whether the RA's preference-elicitation method made users feel in control [Bechwati and Xia 2003].

3.4 Experimental Tasks

The two tasks given to participants were (1) to choose a printer as a birthday present for a family member and (2) to select a printer as a wedding gift for a best friend. The order of the two tasks was counterbalanced. The family member in the experimental task was described as a novice user who had little experience or knowledge of printers and who wanted a printer for occasional home use. The friend was characterized as an experienced user who had substantial experience and knowledge of printers and would use the printer in his/her work. To ensure the independence of the two tasks, we included a break lasting several minutes between the two tasks. During the break, the mobile device was reset so that participants could not simply revise what they did during the first task. In addition, the research assistant emphasized that participants needed to make a decision for another person who had different preferences than the first person. Thus, the two tasks were performed independently. No definite price limits were set for either of the tasks as participants given price limits may eliminate alternatives exceeding the price limit, thereby being unintentionally driven to prefer RA-AT over RA-AL. However, a complete lack of price constraints would not mimic the reality of purchase efforts in which buyers must strive to save money while finding a product that satisfies all their preferences. Thus, we asked participants to consider an appropriate price range (based on the availability of products at the store) for each of the tasks and provide it as a factor to justify their choices upon completion of the experimental session.

3.5 Desirable vs. Less Desirable Printers

For the two types of printer users, the Canon Pixma iP5200 and the HP Photosmart 8050 were deemed the best printers based upon the attribute levels and reviews by consumer magazines. Table II shows all attribute levels for each printer except operating systems, as all 22 printers support both of the two major operating systems (Windows and Mac OS). Two products, the Canon Pixma iP5200 and the HP Photosmart 8050, showed better values in

many attributes than other products. Adding up all attribute levels, the Canon Pixma iP5200 has the highest total score (20 points); the HP Photosmart 8050 has the second highest (18 points). The highest total scores provide a strong indication that these two products are better than other printers in many aspects.

As shown in Table II, the Canon excelled in such attributes as quality, speed, and savings on cartridge costs, considered the most important attributes by expert users; indeed, *Consumer Reports* (July 2006, page 37) selected the Canon Pixma iP5200 as "the best all-around performer," noting that, "The Canon (Pixma iP5200) stands out for quality, low print costs, and speed. Photos and text were excellent." The attributes for which the Canon had the lowest levels (i.e., 1 out of 2 for portability and availability of media card slots) were not critical to the expert users described in the experimental task.

The HP Photosmart 8050 was less expensive ($ 125.46) than the Cannon Pixma iP5200 ($ 199.95) and had above-average attributes (as shown in Table II). It scored the lowest for portability, which did not matter to the novice user described in the task. *PC Magazine* (March 2006) ranked the HP Photosmart 8050 among the top five photo printers of the year, along with the Canon Pixma iP5200.[6] In addition, *MacWorld* (November 2005) reviewed the Photosmart as the best base model.[7]

3.6 Store Design

We conducted the experiment in a controlled laboratory setting instead of a real store to control for any potential extraneous confounding variables existing in a real store (e.g., background music, encounters with salespeople and other shoppers). The store was made to appear as realistic as possible for the participants (see Figure 3). The pictures of 22 printers were displayed on the shelves within the store. Because of a number of issues related to budget and logistics, we chose to display life-size pictures of printers rather than real printers. The use of pictures instead of real products has been widely implemented in other studies investigating in-store purchase choices in a laboratory (for example, see Van Der Heijden [2006]). A product tag was placed under each item and affixed to the shelves such that participants could not move tags around to cross-examine product information (see Figure 3).

3.7 Participants and Experimental Procedures

A total of 75 students at a large North American university participated in the experiment. Twenty-five participants were randomly assigned to each of the three treatment groups. As the current study focused on nonexpert users, we controlled the participants' previous knowledge of the product category by

[6]http://www.pcworld.com/article/123932-1/article.html.
[7]http://www.macworld.com/2005/11/reviews/photosmart8050/index.php.

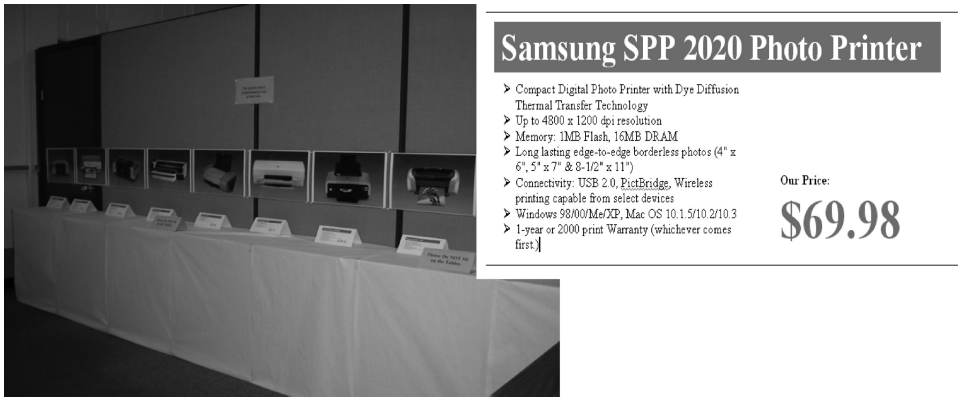

Fig. 3. Simulated store and a price tag used.

recruiting only those who (1) had not purchased a printer in the last two years, (2) had not previously owned the same printer models used in the study, and (3) had little or no expertise with printers (1 to 4 on a 7-point printer expertise scale ranging from 1, not at all expert, to 7, extremely expert). Each participant was guaranteed monetary compensation for his/her participation ($20). To increase participants' involvement, we offered an additional incentive of $40 to the top 25% of participants who justified their choices most convincingly and reasonably.

The experimental session began with a training session. Each participant watched a tutorial video that described how to use a given RA. Then, a research assistant trained participants to use each of the features of the RA. Next, participants were asked to complete each of their two shopping tasks in two stages, to closely mimic the typical purchase decision patterns in a real store. Recall the sequence of in-store decision making described by Russo and Leclerc [1994] (as explained in Section 2.5.3): upon entering the store, consumers briefly scan products displayed on the shelves to familiarize themselves with the available alternatives and the physical layout of the store. To ensure that participants briefly scanned the products in the artificial store, which displays pictures of products rather than real products, we created the two-staged shopping. In Stage 1, participants in all the three treatment groups, including those in the nonRA group, were asked to familiarize themselves with the products without the RA. Participants were asked to behave as if they had just arrived at the store and to walk around to see what was available on the shelves without making a purchase decision. Next, participants in the two RA groups were provided with the handheld device on which the RA was running and continued to Stage 2, when they were instructed to make a purchase decision while using the RA at least once. Participants in the nonRA group were also instructed to continue to Stage 2 to make the final choices, but without the use of the RA. Upon completion of task 1, participants repeated the same processes for task 2. Once all participants had finished their two tasks, they were asked to complete an online questionnaire.

Table III. Results of the Hypothesis Testing

	H1a, H1b, H6	H2a, H2b	H3a, H3b, H7	H4	H5
	Decision-Making Time	Perceived Effort	Decision Accuracy	Pattern of Information Acquisition	Perceived Control
	Time Spent	Seven-point semantic scale	Choice of desirable printers	Analyses of shopping behaviors	Seven-point semantic scale
Non-RA	23.08 min (SD[9] = 8.76)	3.70 / 7.00 (SD = .62)	2 for task 1; 12 for task 2	N/A	N/A
RA-AL	38.60 min (SD = .9.38)	3.24 (SD = .65)	9 for task 1; 17 for task 2	18 acquired information from the two sources	5.89 / 7.00 (1.02)
RA-AT	35.68 min (SD = 9.38)	3.13 (SD = .44)	3 for task 1; 10 for task 2	2 acquired information from the two sources	5.32 / 7.00 (1.02)
Method used	ANCOVA	ANCOVA	Chi-square test	Chi-square test	ANCOVA
RA-AL vs. Non-RA	$F(1,41^{10}) = 26.12, p < .001$	$F(1,42) = 11.27, p < .01$	χ^2 (2,N = 50) = 6.50, $p < .05$	N/A	N/A
RA-AT vs. Non-RA	$F(1,41) = 18.82, p < .001$	$F(1,42) = 5.88, p < .05$	χ^2 (2,N = 50) = .83, p > .05	N/A	N/A
RA-AL vs. RA-AT	$F(1,42) = 1.31, p > .05$	N/A	χ^2 (2,N = 50) = 7.12, $p < .05$	χ^2 (2,N = 43) = 30.56, $p < .001$	$F(1,42) = 4.70, p < .05$
Hypotheses Supported					
H1a* **	**RA-AL users will spend more time making decisions than RA nonusers.**				
H1b* **	**RA-AT users will spend more time making decisions than RA nonusers.**				
**H2a ** **	**RA-AL users will perceive less effort in making product choice decisions than RA nonusers.**				
**H2b * **	**RA-AT users will perceive less effort in making product choice decisions than RA nonusers.**				
H3a*	**RA-AL users will make more accurate product choice decisions than RA nonusers.**				
H3b (N.S)	RA-AT users will make more accurate product choice decisions than RA nonusers.				
H4* **	**RA-AL users, as compared to RA-AT users, will acquire information from products displayed on shelves in the phase of screening products.**				
H5*	**RA-AL users will perceive higher control over the decision-making processes than RA-AT users.**				
H6 (N.S)	**RA-AL users will spend less time making decisions than RA-AT users.**				
H7*	**RA-AL users will make more accurate product choice decisions than RA-AT users.**				

***, **, and * indicates that the hypothesis is supported at the .001, .01, and .05 significance levels, respectively. N.S. refers to "not significant"; thus, the hypothesis is not supported.

4. RESULTS AND ANALYSES

4.1 Hypothesis Testing

Cronbach's alpha to assess the reliability of perceived effort and perceived control was 0.86 and 0.78, respectively, exceeding the recommended level of 0.7 [Barclay et al. 1995]. The results of the hypothesis testing are presented in Table III.

First, RA-AL and RA-AT users were contrasted to RA nonusers in terms of decision making time spent using an ANCOVA.[8] Factors that can potentially influence users' perceptions of the RAs, including consumers' current Web usage frequency, previous Web experience, gender, tendency to pursue accuracy

[8]In the subsequent analyses, we did not separate results for shopping tasks 1 and 2, except for decision accuracy, because there was no difference between the two tasks.

[9]SD: Standard Deviation.

[10]One data point was missing from the RA non-user group.

Table IV. Printers Chosen for a Family Member

	Printer models	Price (in Canadian dollars)	Groups			Total
			RA-AL	RA-AT	Non-RA	
Desirable printer	HP Photosmart 8050	125.46	9	3	2	14
Less desirable printers	Lexmark Z517	39.98	1		2	3
	Samsung SPP 2020 Photo	69.98	1		1	2
	Canon Pixma iP1600	79.73	2	1	2	5
	HP Deskjet 5440	89.91	3	2	1	6
	Canon Pixma iP6210D	97.00	4	6		10
	Epson Stylus C88	99.92			5	5
	HP Photosmart 335	99.92		5	3	8
	Canon Pixma iP6220D	127.00	1	2	1	4
	HP Deskjet 5940	129.42		1	3	4
	HP Deskjet 6940	144.86	1		1	2
	Canon Pixma iP4200	149.36			1	1
	Canon Selphy DS810	179.92		1		1
	Canon Pixma iP5200	199.96	3	2	1	6
	HP Officejet Pro K550	229.95			1	1
	Epson Stylus Photo R340	249.92		1		1
	HP Photosmart 8250	249.92		1	1	2
Total			25	25	25	75

over effort, involvement with printers, and previous experience with handheld devices, were controlled. As expected, RA nonusers spent significantly less time than both RA-AL users ($F(1, 41) = 26.12, p < .001$) and RA-AT users ($F(1, 41) = 18.82, p < .001$). Thus, H1a and H1b were supported.

RA-AL and RA-AT users were then compared to RA nonusers in terms of perceived effort. The result of ANCOVA with the same control variables shows that, despite the longer actual decision-making time, both RA-AL and RA-AT users perceived less effort than RA nonusers ($F(1, 42) = 11.27, p < .01$; $F(1, 42) = 5.88, p < .05$, respectively), supporting H2a and H2b.

We compared decision accuracy among RA-AL, RA-AT, and RA nonusers by conducting chi-square tests. We first analyzed decision accuracy between RA-AL users and RA nonusers. The chi-square test-result shows that RA-AL users made significantly more accurate decisions than RA nonusers (χ^2 (2, N = 50) = 6.50, $p < .05$), supporting H3a. However, RA-AT users' decision accuracy did not differ from RA nonusers (χ^2 (2, N = 50) = .083, $p > .05$), thus rejecting H3b.

Next, we compared RA-AL and RA-AT. The difference in decision-making time between the RA-AL and RA-AT users was not significant ($F(1, 42) = 1.31$, $p > .05$), rejecting H7 that RA-AL users exert less effort than RA-AT users. In contrast, the difference in decision accuracy between RA-AL and RA-AT was significant (χ^2 (2, N = 50) = 7.12, $p < .05$), supporting H8, which states that RA-AL users will make more accurate decisions than RA-AT users. A closer look at the choices made by RA-AL and RA-AT users further clarifies this difference; Tables IV and V compare the number of participants across the three groups who chose the two most desirable printers versus the number who chose other printers. RA-AL users chose the desirable printers more often than participants in the other two groups. RA nonusers and RA-AT users showed somewhat similar choice patterns. Specifically, for the task "choose a printer for a family

Table V. Printers Chosen for a Best Friend

	Printer models	Price (in Canadian dollars)	Groups			Total
			RA-AL	RA-AT	Non-RA	
Desirable printer	Canon Pixma iP5200	199.96	17	10	12	39
Less desirable printers	HP Deskjet 5440	89.91		1		1
	Canon Pixma iP6210D	97.00	1			1
	Epson Stylus C88	99.92			1	1
	HP Photosmart 335	99.92	1	1	1	3
	Lexmark P315	99.93			1	1
	HP Photosmart 8050	125.46	2	3	3	8
	HP Deskjet 6940	144.86		2	1	3
	HP Officejet Pro K550	229.95	1		1	2
	Epson Stylus Photo R340	249.92	1	2	3	6
	HP Photosmart 8250	249.92		3	2	5
	Epson Picturemate	249.93		1		1
	Canon Pixma iP6600D	269.92	2			2
	HP Deskjet 9800	399.95		2		2
Total			25	25	25	75

member (i.e., a novice user)," 9 RA-AL users chose the most desirable printer (HP Photosmart 8050), compared to only 3 RA-AT users and 2 RA nonusers. For the task "select a printer for a friend (i.e., an expert user)," 17 RA-AL users chose the most desirable printer (Canon Pixma iP5200), compared to 10 RA-AT users and 12 RA nonusers. In sum, the differences are salient between the RA-AL group and the others, contrary to the expectation that the difference between RA nonusers and the two RA user groups would be significant.

Finally, we compared RA-AL and RA-AT users' decision-making processes. First, we counted how many RA-AL and RA-AT users inspected products on the shelves during the phase of screening products. As previously stated, we were able to film only 23 RA-AL users and 20 RA-AT users due to equipment failures; 18 out of 23 RA-AL users inspected product displays on the shelves in the two experimental tasks whereas only 2 of the 20 RA-AT users did so. The chi-square test result indicated a significant difference between the RA-AL and RA-AT groups: $\chi^2\,(2, \mathrm{N} = 43) = 21.392, p < .001$. This result supports H4, which states that, during the phase of screening, RA-AL users acquire information not only from the RA, but also from product displays, whereas RA-AT users acquire information from the RA only without looking at product displays.

Finally, H5 regarding perceived control between RA-AL and RA-AT was tested using an ANCOVA with the same control variables. The result supported H5, indicating that RA-AL users felt more perceived control than RA-AT users ($\mathrm{F}(1, 42) = 4.702$, $p < .05$).

4.2 Follow-Up Study

The results from the main experiment support that RA-AL users perceived higher control (H5) and made more accurate decisions (H7) than RA-AT users in the store. In our attempt to support these significant results, we conducted a follow-up study to demonstrate that the RA-AL's fit with in-store consumers' information-processing patterns was the main cause of their higher perceived

control and decision accuracy. If the fit was the main cause, RA-AL users' perceived control and decision accuracy should decrease out of the store (where such fit does not exist and therefore the positive effects of the fit do not occur) as compared to their perceived control and decision accuracy in the store. In contrast, RA-AT users' perceived control and decision accuracy should increase out of the store (where they do not experience the negative effects of the misfit) as opposed to in the store.

In this follow-up experiment, all conditions were kept the same as the main experiment, including the mobile handheld devices, Wi-Fi connection, the set of printers, participants' training and background, experimental procedures, and incentives. The only difference is that participants used the mobile RAs in a laboratory setting that resembled a common office setting in which a chair and desk are located within a cubicle, and there were no products or store shelves. Because of the lack of product displays, each of the two shopping tasks was conducted in one continuous phase, not in two discrete phases as, without products displayed on shelves, we could not implement the first stage in which participants inspect products displayed on shelves without the mobile devices. Twenty participants were recruited, with 10 subjects allocated randomly to each RA. Because of the small sample size (10 per cell, 20 total), caution must be exercised in interpreting the results from the follow-up study; they should be used only as further support of our hypothesis testing of H5 and H7 discussed in the previous section.

The results are displayed in Figures 4, 5, and 6. The general pattern for perceived control and accuracy is that RA-AL users perceived lower control and made less accurate decisions out of the store than in the store; in contrast, RA-AT users perceived slightly higher control and made more accurate decisions out of the store than in the store. The ANCOVA results (with the same control variables used in the main experiment) showed that the difference in RA-AL users' perceived control between in- and out-of-the-store conditions was statistically significant ($F(1, 27) = 4.73, p < .05$). RA-AL users' decision accuracy was significantly higher in the store than out of the store for the task involving a family member (χ^2 (1, N = 35) = 3.14, $p < .10$) as well as for the task involving the best friend (χ^2 (1, N = 35) = 2.80, $p < .10$).[11]

In contrast, ANCOVA results did not indicate a significant difference in RA-AT users' perceived control between in- and out-of-the-store conditions ($F(1, 27) = .26$, $p > .10$). Likewise, RA-AT users did not show a significant difference in decision accuracy for the task involving a family member (χ^2 (1, N = 35) = .60, $p > .10$), or for the task involving the best friend (χ^2 (1, N = 35) = .48, $p > .10$),[12] between in- and out-of-the-store conditions.

These results support the notion that the fit between RA-AL's alternative-driven approach and in-store consumers' information processing pattern caused RA-AL users to perceive higher control and to make more accurate

[11]A correction for continuity is applied to prevent overestimation of statistical significance for a 2×2 table with a cell that has an expected count less than five [Yates 1934].

[12]A correction for continuity is applied to prevent overestimation of statistical significance for a 2×2 table with a cell that has an expected count less than five [Yates 1934].

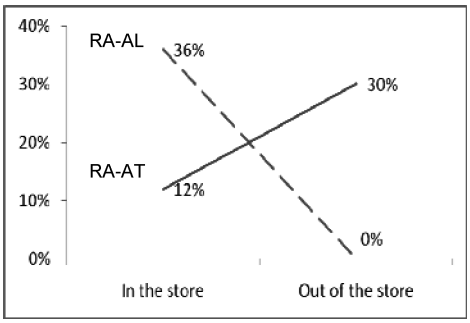

Fig. 4. Percentage of participants who chose the desirable printer for a family member.

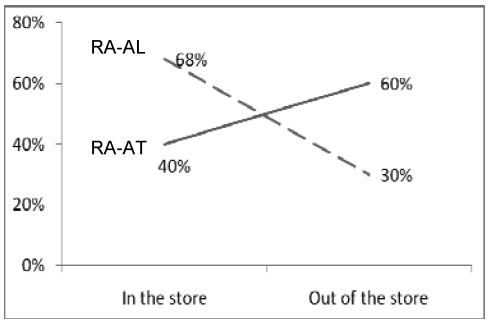

Fig. 5. Percentage of participants who chose the desirable printer for the best friend.

decisions in the store. Out of the store where no positive impact of fit occurred, RA-AL indeed felt having less control and made less accurate decisions. However, RA-AT users' perceived control and decision accuracy between in- and out-of-the-store conditions were not *statistically* different. This is contrary to our expectations that RA-AT users would perform better out of the store where there are no negative consequences of the misfit. We believe that the non-significant results are mainly caused by the small sample size, because, as shown in Figures 4, 5, and 6, RA-AT users showed a performance increase out of the store. Future researchers should address this issue with an adequate sample size for statistical power.

4.3 Post-Hoc Analysis

In order to further explain why RA-AT users made less accurate decisions than RA-AL users in the store, we analyzed decision-making processes of the two types of RA users. Particularly, we analyzed which decision strategies, namely, compensatory versus noncompensatory strategies, RA-AT users employed. The compensatory strategy leads to more accurate decisions while the noncompensatory leads to less accurate ones, as explained in section 2.1 [Payne et al. 1993]. Note that RA-AT (as well as RA-AL) is built based upon the two strategies and thus RA-AT (as well as RA-AL users) could have applied both compensatory

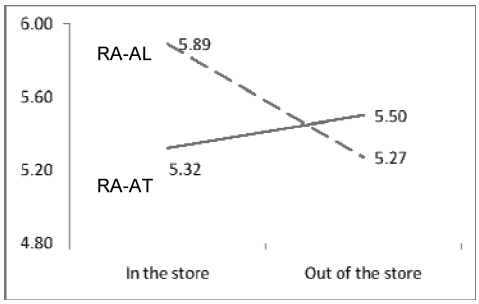

Fig. 6. Perceived control (seven-point scale).

and noncompensatory strategies.[13] When given many decision strategies from which to choose, individuals choose a strategy that is the most appropriate for their current circumstances [Payne et al. 1993]. Likewise, one can expect that the RA-AT users chose strategies that appear to them the most appropriate for their particular circumstances.

Recall that RA-AT users experience the misfit between their information-processing pattern and RA-AT's attribute-driven approach. Because the misfit increases complexity of decision tasks, RA-AT users will be led toward a noncompensatory strategy, such as eliminating products that do not meet their specified levels [Slovic et al. 1990]. This is because eliminating alternatives by aspect is easier and reduces their effort; consequently, it is more appealing to users who experience cognitive burden. Specifically, in-store RA-AT users, irritated by the need to align the two incompatible sources, grow more intent on using the "extremely important" level in the hopes of getting to the alternative they would like to observe more quickly. The use of the "extremely important" level indicates the use of elimination-based noncompensatory strategies. Meanwhile, out-of-store RA-AT users are not troubled by the misfit, and thus become less inclined to use the "extremely important" level.

As expected, the results of the main and follow-up experiments showed an increase of the number of RA-AL users who facilitated the elimination-based

[13]RA-AT and RA-AL are built based upon both compensatory and non-compensatory strategies. First, recall that the RA-AT user reviews information about products from the list of printers and then retains the printers that seem like good candidates. At this point, the user can employ both compensatory (e.g., additive difference or weighted additive strategy) and noncompensatory strategies (e.g., conjunctive, satisfying, elimination-by-aspect [EBA] strategies). Next, comparing products pairwise, the user can apply either additive difference and/or majority of confirming dimensions strategies, the two compensatory strategies utilized for pairwise comparisons. Finally, RA-AL applies the equal weight strategy to find the alternatives with values similar to those of the user-chosen product. Likewise, RA-AT users can employ both compensatory (weighted additive strategy) and noncompensatory strategies (EBA strategy). Recall that RA-AT requires users to indicate first their preferred attribute levels and then the importance of these attributes in their purchases. Here, if consumers choose the level "extremely important," any alternatives that do not meet this level are eliminated; thereby the EBA strategy is applied. The choices of lower importance levels, that is, "important" and "somewhat important," lead to the use of a simplified weighted additive strategy. Further information about the decision strategies can be found in Payne et al. [1993].

noncompensatory strategy in the store as opposed to out of the store. For the task of choosing a printer for a family member, only three out of 10 RA-AT users employed the elimination-based noncompensatory strategy out of the store (30% of RA-AT users), while 11 out of 25 RA-AT users did so in the store (44% of RA-AT users). Likewise, for the task of choosing a printer for the best friend, two out of 10 RA-AT users employed the elimination-based noncompensatory strategy out of the store (20% of RA-AT users), whereas 13 out of 25 RA-AT users employed it in the store (52% of RA-AT users). These results support our claim that the misfit leads in-store RA-AT users to the use of non-compensatory strategies, which in turn results in inaccurate choices.

5. DISCUSSION AND CONCLUSIONS

5.1 Summary of the Findings

The purpose of this study was twofold: to empirically test whether mobile RAs enhance users' in-store purchase decisions and to evaluate two common types of interactions provided by RAs to demonstrate that the interaction compatible with the task undertaken enhances users' decision-making processes, thereby leading to better decision performance.

We compared mobile RA use and RA nonuse because in-store consumers experience severe information overload due to the influx of information in retail stores; mobile RAs should effectively reduce the overload, thereby helping consumers reach better quality decisions. However, whether the use of mobile RAs reduces the overload was not clear because using the small and limited input/output facilities of a mobile device, particularly while physically moving around in a store, increases the user's effort. The results from our experiment show that the increase in the objective amount of effort is not translated into the subjective effort that consumers feel as interacting with mobile RAs is engaging and involving, and users share the workload with the mobile RAs. However, RA users overall did not uniformly make more accurate decisions than RA nonusers. Only RA-AL users made more accurate decisions, while RA-AT users had no statistically difference use compared to RA nonusers. This result leads us to question what particular aspects of the interactions afforded by the two mobile RAs yielded such differences in users' decision accuracy.

RA-AL users, compared to RA-AT users, acquired information from products on shelves more effectively when screening products. Furthermore, they felt that they were more in control compared to RA-AT users. These results suggest that the interactions built in RA-AL better fit the user's in-store purchase decision, thereby facilitating product examinations from multiple sources. Because RA-AL users examined and reviewed products effectively, they learned about products better than RA-AT users and, consequently, made more accurate decisions. These results demonstrate the importance of fit between interactions afforded by mobile RAs and the task the user performs in the context. Because mobile applications are used for a particular task situated in a dynamic context, the fit between the interactions embedded in the mobile application and the context serves as a catalyst for user performance.

However, contrary to our expectations, RA-AL users did not spend less time than RA-AT users, despite the better fit. In hindsight, RA-AL's alternative-driven approach may have caused participants to evaluate their chosen alternatives one by one, whereas RA-AT's attribute-driven approach helped them reduce the consideration set quickly. A judgment task based on the evaluation of alternatives requires more effort than a choice task based on elimination by aspect [Johnson and Russo 1981]. Therefore, RA-AL saved users effort by providing congruent guidance, but this was countermanded by users' effort to evaluate products.

5.2 Limitations

This study has several limitations, beginning with the artificiality of a store setting created in a laboratory. The purchase setting created in the lab might not properly reflect distractions, ambient noises, and encounters with other shoppers and salespeople in authentic store settings. Nonetheless, our major intention was to test the effects of fit between RAs' interactions and consumers' in-store information processing, and we needed to control other variables that might have affected the results. In addition, we used pictures of printers instead of real printers for numerous practical reasons, including the difficulty of returning printers after the experiment. However, printers have many search attributes consumers can examine sufficiently without direct contact with the product [Suh and Lee 2005]; therefore, use of pictures would not have affected the results. The two-stage shopping (first reviewing products, then making purchase decisions) may also have been artificial. However, such distinction was made to ensure that participants' shopping behaviors closely reflected their real choice processes as theorized by a prior study [Russo and Leclerc 1994]. The conceptualization of desirable printers versus less desirable printers is clearly limited in the sense that, strictly speaking, the desirable printers are not nondominated products. However, we used real printers and, in any efficient market, nondominated products do not exist because conflicts among attributes are inevitable [Haubl and Murray 2003]. Therefore, the use of real printers increases the realism of the experiment. Last but not least, the results cannot be generalized to all implementations of alternative- versus attributed-driven RAs. In this study, we compared two particular implementations of the alternative- versus attribute-driven approaches. Thus, the results may not generalize to different implementations.

5.3 Contributions and Implications

This study makes important contributions to both theory and practice. First, except for Van der Heijden's [2005] work, very few studies have investigated particular design elements of mobile RAs that influence in-store purchase decisions. To the best of our knowledge, this is the first study equipped with fully functional and interactive preference-elicitation methods to examine user shopping behaviors in a store. Second, this study has shown that attribute-driven interactions, the dominant design for web-based shopping, is not congruent with the way in which users examine products on shelves and hence, is not suitable for in-store purchase contexts.

Based upon this study, mobile RA designers should consider the alternative-driven interaction, which has been largely neglected in web-based shopping. RA-AL does not require as much cost and expertise to develop as RA-AT. RA-AL designers do not need to develop a complicated algorithm for a preference-elicitation method because the main role of RA-AL is to support users in making their own side-by-side comparisons by generating recommendations by simply inferring consumers' preferences based upon the products they choose. Thus, an alternative-driven RA reduces the cost of development while increasing the quality of service it provides to in-store consumers.

5.4 Future Research

Future researchers may consider conducting a field experiment to overcome, via triangulation, the apparent limitations of investigating in-store decisions in a laboratory. Researchers may want to explore further the effects of fit on decision-making efforts in order to resolve the questions left unanswered in this study, more specifically, to explicitly compare the effort saved by fit and the effort increased by fit (i.e., users inspect more products).

In this study, we considered only the user task in a store environment as the important element for designing mobile RAs. Future researchers should consider additional elements, such as context, content, community, customization, communication, connection, and commerce, the 7 Cs of customer interfaces for electronic commerce [Rayport and Jaworski 2001]. For instance, users may consider it important to stay connected with members of the community to which they belong and thus may find mobile RAs that provide community features more helpful. In this sense, the role of mobile RAs is to enable users to communicate with their friends about particular products in which they are interested rather than provide information and recommendations. Moreover, the information provided by mobile RAs can be customized based upon users' past purchase history, location, and expertise in the product category.

REFERENCES

ABRATT, R. AND GOODEY, S. D. 1990. Unplanned buying and in-store stimuli in supermarkets. *Manage. Decision Econo. 11*, 111–121.

ALBERS, M. J. AND KIM, L. 2000. User Web browsing characteristics using palm handhelds for information retrieval. In *Proceedings of the 18th Annual ACM International Conference on Computer Documentation: Technology & Teamwork. IEEE*. 125.

BARCLAY, D., THOMPSON, R., AND HIGGINS, C. 1995. The partial least squares (PLS) approach to causal modeling: Personal computer adoption and use as an illustration. *Technol. Studies 2*, 285–309.

BECHWATI, N. N. AND XIA, L. 2003. Do computers sweat? The impact of perceived effort of online decision aids on consumers' satisfaction with the decision process. *J. Consum. Psych. 13*, 139–148.

BETTMAN, J. R., JOHNSON, E. J., LUCE, M. F., AND PAYNE, J. W. 1993. Correlation, conflict, and choice. *J. Experi. Psych.: Learn. Memory, Cognition 19*, 931–951.

BETTMAN, J. R., LUCE, M. F., AND PAYNE, J. W. 1998. Constructive consumer choice processes. *J. Consum. Resear. 25*, 187–217.

BETTMAN, J. R. AND ZINS, M. A. 1979. Information format and choice task effects in decision making. *J. Consum. Resear. 6*, 141–153.

BIEHAL, G. AND CHAKRAVARTI, D. 1982. Information-presentation format and learning goals as determinants of consumers' memory retrieval and choice processes. *J. Consum. Resear. 8*, 431–441.

BROWN, D. L. AND JONES, D. R. 1998. Factors that influence reliance on decision aids: A model and an experiment. *J. Inform. Syst. 12*, 75–94.

BRUCKS, M. 1985. The effects of product class knowledge on information search behavior. *J. Consum. Resear. 12*, 1–16.

COHEN, J. 1960. A coefficient for agreement for nominal scales. *Edu. Psych. Measur. 20*, 37–46.

DESMET, P. AND RENAUDIN, V. 1998. Estimation of product category sales responsiveness to allocated shelf space. *Int. J. Resear. Market. 15*, 443–457.

DIEHL, K. 2005. When Two rights make a wrong: Searching too much in ordered environments. *J. Market. Resear. 42*, 313–322.

DIX, A., RODDEN, T., DAVIES, N., TREVOR, J., FRIDAY, A., AND PALFREYMAN, K. 2000. Exploiting space and location as a design framework for interactive mobile systems. *ACM Trans. Comput.-Hum. Interact.* 285–321.

EIERMAN, M. A., NIEDERMAN, F., AND ADAMS, C. 1995. DSS Theory: A model of constructs and relationships. *Decision Supp. Syst. 14*, 1–26.

FRESE, M., ULICH, E., AND DZIDA, W. 1987. A theory of control and complexity: implications for Software design and integration of computer systems into the work place. In *Psychological Issues of Human-Computer Interaction in the Workplace*, M. Frese, Ed. Elsevier Science, 313–337.

GOODHUE, D. L. 2006. Task-technology fit. In *Human-Computer Interaction and Management Information Systems: Foundations*, P. Zhang and D. Galletta, Eds. M.E. Sharpe, A. 184–204.

HAUBL, G. AND MURRAY, K. B. 2003. Preference construction and persistence in digital marketplaces: The role of electronic recommendation agents. *J. Consum. Psych. 13*, 75–91.

HAUBL, G. AND TRIFTS, V. 2000. Consumer decision making in online shopping environments: The effects of interactive decision aids. *Market. Sci. 19*, 189–200.

HOFFMAN, D. L. AND NOVAK, T. P. 1996. Marketing in hypermedia computer-mediated environments: Conceptual foundations. *J. Market. 60*, 50.

HONG, W., THONG, J. Y. L., AND TAM, K. Y. 2004. The effects of information format and shopping task on consumers' online shopping behavior: A cognitive fit perspective. *J. Manage. Inform. Syst. 21*, 149–184.

HUANG, Z., CHEN, H., GUO, F., XU, J. J., WU, S., AND CHEN, W.-H. 2006. Expertise visualization: An implementation and study based on cognitive fit theory. *Decision Supp. Syst. 42*, 1539–1557.

HUFFMAN, C. AND KAHN, B. 1998. Variety for sale: mass customization or mass confusion? *J. Retail. 74*, 491–513(423).

JOHNSON, E. J. AND RUSSO, J. E. 1978. The organization of product information in memory identified by recall times. *Advances Consumer Resear. 5*, 79–86.

JOHNSON, E. J. AND RUSSO, J. E. 1981. Product familiarity and learning new information. *Advances Consumer Resear. 8*, 151–155.

JOSHI, A. 2000. On mobility and agents. In *Mobile Networks and Computing*, S. Rajasekaran, P. Pardalos and D. F. Hsu, Eds., American Mathematical Society, 161–170.

KAMIS, A., KOUFARIS, M., AND STERN, T. 2008. Using an attribute-based decision support system for user-customized products online: An experimental investigation. *Manage. Inform. Syst. Quart. 32*, 19.

KOMIAK, S. Y. X. AND BENBASAT, I. 2006. The effects of personalization and familiarity on trust in and adoption of recommendation agents. *Manage. Inform. Syst. Quart. 30*, 941–960.

KOWATSCH, T. AND MAASS, W. 2010. In-store consumer behavior: How mobile recommendation agents influence usage intentions, product purchases, and store preferences. *Comput. Hum. Behav. 26*, 697–704.

KUNDE, W. 2003. Temporal response-effect compatibility. *Psych. Resear. 67*, 153–159.

LEE, Y. E. AND BENBASAT, I. 2003. Interface design for mobile commerce. *Comm. ACM 46*, 48–52.

LO, C.-C., KUO, T.-H., KUNG, H.-Y., KAO, H.-T., CHEN, C.-H., WU, C.-I., AND CHENG, D.-Y. 2010. Mobile merchandise evaluation service using novel information retrieval and image recognition technology. *Comput. Comm.*

LYNCH JR, J. G. AND SRULL, T. K. 1982. Memory and attentional factors in consumer choice: Concepts and research methods. *J. Consum. Resear. 9*, 18–37.

MARCUS, A. 2001. Babyface design for mobile devices and the web. In *Proceedings of the 9th International Conference on Human-Computer Interaction*, M. J. Smith and G. Salvendy, Eds. Lawrence Erlbaum Associates, 514–518.

MCLAUGHLIN, A. C., ROGERS, W. A., AND FISK, A. D. 2009. Using direct and indirect input devices: Attention demands and age-related differences. *ACM Trans. Comput. Hum. Interact.*, 1–15.

MILLER, B. N., ALBERT, I., LAM, S. K., KONSTAN, J. A., AND RIEDL, J. 2003. MovieLens Unplugged: Experiences with an occasionally connected recommender system. In *Proceedings of the International Conference on Intelligent User Interfaces*, L. Johnson and E. Andre, Eds. 263–266.

MILLER, Z. 2009. Gone in 2.3 seconds: Capturing shoppers before they disappear. Z. Miller, Ed. *Miller Zell Research.*

MORRIS, S. A. AND MARSHALL, T. E. 2004. Perceived control in information systems. *J. Organizat. End User Comput. 16*, 38–56.

O'HARA, K. AND PERRY, M. 2001. Shopping anytime anywhere. In *Proceedings of the Conference on Human Factors in Computing System*.

OLSON, E. L. AND WIDING, R. E. 2002. Are interactive decision aids better than passive decision agents? A comparison with implications for information providers on the internet. *J. Interact. Market. 16*.

PAYNE, J. W., BETTMAN, J. R., AND JOHNSON, E. J. 1993. *The Adaptive Decision-Maker*. Cambridge University Press, Cambridge, U.K.

PHILLIPS, H. AND BRADSHAW, R. 1993. How customers actually shop: customer interaction with the point of sale. *J. Market Resear. Soc. 35*, 51–62.

RAYPORT, J. AND JAWORSKI, B. 2001. *Introduction to E-Commerce.* McGraw-Hill, New York.

RIEDL, J. AND DOURISH, P. 2005. Introduction to the special section on recommender systems. *ACM Trans. Comput. Hum. Interact. 12.3*, 371–373.

RUSSO, J. E. 1977. The value of unit price information. *J. Market. Resear. 14*, 193–201.

RUSSO, J. E. AND DOSHER, B. A. 1983. Strategies for multiattribute binary choice. *J. Exper. Psych. Learn. Mem. Cognit. 9*, 676–696.

RUSSO, J. E. AND LECLERC, F. 1994. An eye-fixation analysis of choice processes for consumer nondurables. *J. Consumer Resear. 21*, 274–290.

RUSSO, J. E., STAELIN, R., NOLAN, C. A., RUSSELL, G. J., AND METCALF, B. L. 1986. Nutrition information in the supermarket. *J. Consumer Resear. 13*, 48–70.

SENGUPTA, K. AND TE'ENI, D. 1993. Cognitive feedback in GDSS: Improving control and convergence. *Manage. Inform. Syst. Quart. 17*, 87.

SLOVIC, P. 1995. The construction of preference. *Amer. Psych. 50*, 364–371.

SLOVIC, P., GRIFFIN, D., TVERSKY, A., AND HOGARTH, R. 1990. Compatibility effects in judgment and choice. In *Insights in Decision Making: A Tribute to Hillel J. Einhorn*, R. Hogarth, Ed. University of Chicago Press, Chicago, 5–27.

SONG, J., JONES, D., AND GUDIGANTALA, N. 2007. The effects of incorporating compensatory choice strategies in web-based consumer decision support systems. *Decis. Supp. Syst. 43*, 359–374.

SUAREZ, M. 2005. Shelf space assigned to store and national brands: A neural networks analysis. *Int. J. Retail Distri. Manage. 33*, 858–878.

SUH, K. S. AND LEE, Y. E. 2005. The effects of virtual reality on consumer learning: An empirical investigation. *Manage. Inform. Syst. Quart. 29*, 673–697.

SVENSON, O. 1979. Process descriptions of decision making. *Organiz. Behav. Hum Decis. Proc. 23*, 86–112.

SWAMINATHAN, V. 2002. The impact of recommendation agents on consumer evaluation and choice: The moderating role of category risk, product complexity, and consumer knowledge. *J. Consumer Psych. 13*, 93–101.

UNDERHILL, P. 1999. *Why We Buy: The Science of Shopping.* Simon & Schuster, New York.

VAN DER HEIJDEN, H. 2006. Mobile decision support for in-store purchase decisions. *Decis. Supp. Syst. 42*, 656–663.

VAN DER HEIJDEN, H. AND SORENSEN, J. B. 2002. The mobile decision maker: Mobile decision aids, task complexity, and decision effectiveness. Copenhagen Business School, Frederiksberg, Denmark.

VESSEY, I. 1994. The effect of information presentation on decision making: A cost-benefit analysis. *Inform. Manage. 27*, 103–119.

VESSEY, I. 2006. The theory of cognitive fit. In *Human-Computer Interaction and Management Information Systems: Foundations*, P. Zhang and D. Galletta, Eds. M.E. Sharpe, 141–183.

VESSEY, I. AND GALLETTA, D. 1991. Cognitive fit: An empirical study of information acquisition. *Inform. Syst. Resear. 2*, 63–84.

WANSINK, B., KENT, R. J., AND HOCH, S. J. 1998. An anchoring and adjustment model of purchase quantity decisions. *J. Market. Resear. 35*, 71–81.

XIAO, B. AND BENBASAT, I. 2007. E-Commerce product recommendation agents: Use, characteristics, and impact. *Manage. Inform. Syst. Quart. 31*, 137–209.

YATES, F. 1934. Contingency Table involving small numbers and the chi-square test. *J. Royal Statist. Soc. 1*, 217–235.

YOULL, J., MORRIS, J., AND MAES, P. 2001. Impulse: Location-based agent assistance. In *Proceedings of the International Conference on Web Intelligence.*