

Association for Information Systems AIS Electronic Library (AISeL)

ICIS 2006 Proceedings

International Conference on Information Systems
(ICIS)

December 2006

Personalization: Is It Effective on New and Repeat Users?

Shuk Ho
University of Melbourne

Kar-Yan Tam
Hong Kong University of Science and Technology

Follow this and additional works at: <http://aisel.aisnet.org/icis2006>

Recommended Citation

Ho, Shuk and Tam, Kar-Yan, "Personalization: Is It Effective on New and Repeat Users?" (2006). *ICIS 2006 Proceedings*. 41.
<http://aisel.aisnet.org/icis2006/41>

This material is brought to you by the International Conference on Information Systems (ICIS) at AIS Electronic Library (AISeL). It has been accepted for inclusion in ICIS 2006 Proceedings by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact elibrary@aisnet.org.

PERSONALIZATION: IS IT EFFECTIVE ON NEW AND REPEAT USERS?

General Topics

Shuk Ying Ho

Department of Accounting and Business
Information Systems
University of Melbourne
Australia
suho@unimelb.edu.au

Kar Yan Tam

Department of Information and
Systems Management
Hong Kong University of Science and
Technology, Hong Kong
kytam@ust.hk

Abstract

This work studies personalization from the perspective of human computer interaction. The objectives are to examine the effects of various personalization strategies on users' information processing and decision-making. We commence by reviewing the literature on personalization in the five research domains defined by Banker and Kauffman (2004), and then highlight the debates regarding the effectiveness of personalization in influencing users' decision-making. To bridge the gap between the proliferation of personalization technologies and the uncertainty of their effectiveness, this work addresses the following research question: What are the effects of different personalization strategies on users' information processing? We examine two common personalization strategies: preference matching and set size of personalized content. We explore how these strategies affect users' decision-making. An information processing model rooted in the Heuristic-Systematic Model is developed. We formulate 10 hypotheses on the relationship between personalization strategies and users' information processing. Data collected from two online field studies are used to assess the validity of the proposed hypotheses. The results of the studies indicate that personalization can capture users' attention, and, personalization is also associated with an increase in users' exploration of other content. This effect becomes less salient when the amount of non-personalized content increases.

Keywords: Heuristic Systematic Model, information processing, Web personalization

Introduction

What is Personalization?

Maintaining effective communication with online users is imperative for Internet firms seeking growth and revenue in today's competitive market. Providing responsive and high-quality services is a key factor in achieving a sustainable competitive advantage (Rust and Lemon 2001). As defined by the Personalization Consortium and Cyber Dialogue, personalization is "the use of technology to tailor content to the needs of individual consumers" (Pal and Rangaswamy 2003 pp.33). Personalization technologies are context-aware applications designed to deliver targeted promotions to online users about the products they like and protect them from information overload.

The technology enabler is generally referred to as a personalization agent, which is a collection of software modules that deploys tools to collect and analyze the browsing behavior and purchase transactions of users. These modules, including, data mining, collaborative technology, click stream analysis components, and pattern recognition, allow real-time detection of user behavior and manipulation of Web content (Tam and Ho 2005). With the help of personalization agents, Internet firms can now exert control over and manipulate content-related parameters at a

much finer level than before. Using personalization technologies, Internet firms can ensure that the right person receives the right content in the right format at the right time.

Prior Work on Personalization

Personalization is one of the rapidly emerging technologies in the field of Information Systems (IS) (Adomavicius and Tuzhilin 2005). Studies of personalization technologies in the context of electronic commerce, mobile commerce, and other business channels have been conducted (e.g. Komiak and Benbasat 2006; Tam and Ho 2005; Tam and Ho 2006; Xiao and Benbasat 2006). In the following, we present a review of research studies that deal with personalization and synthesize current knowledge in different areas of IS research. We employ a scheme of surveying literature proposed by Banker and Kauffman (2004), who define five categories of IS research. They are (1) Decision Support and Design Science; (2) Economics of IS and IT; (3) Value of Information; (4) IS Organization and Strategy; and (5) Human Computer Interaction. This scheme is used because it considers not only epistemology but also research methodology.

Work in *Decision Support and Design Science* focuses on the design of personalization systems, mostly in conjunction with processes of personalization. There are studies depicting conceptual frameworks of the operations of personalization systems. These frameworks range from a single system (e.g. Adomavicius and Tuzhilin 2005; Chiasson et al. 2002) to a broader approach involving business-to-business data interchange based on the World Wide Web Consortium (W3C) standards (e.g. Cingil et al. 2000). In addition to conceptual work, there are studies involving development and simulations of personalization systems (e.g. Loia et al. 2006).

There are only a few personalization studies in the next two streams, *Economics of IS and IT* and *Value of Information*. The stream, *Economics of IS and IT*, is related to strategic business units and market economy. One pioneer work is by Murthi and Sarkar (2003), who take an interdisciplinary approach that spans the areas of economics, marketing, information technology, and operations research to address the issues of personalization. They develop a conceptual framework for personalization that allows researchers to identify key players in the personalization process. The framework also examines the strategic role of personalization in the interactions between a firm and other key players in the firm's value chain. The stream, *Value of Information*, uses information economics, real options theory, and information sharing theory to examine firm actions toward personalization applications. An example is the work by Poulin et al. (2006), who study how manufacturers develop capabilities to fulfill the personalization needs under the constraints of price, quality, and service. They propose a framework comprising eight personalization options that could be combined to form a complete personalized offer, and then contrast their impacts on the demand and supply network.

Work in the area of *IS Organization and Strategy* is organization focused. It examines factors affecting the adoption decision of personalization applications. Due to the heterogeneity of organizational and technical circumstances, some firms are still skeptical about personalization applications. This impedes the development of standardized tools. This stream of research examines the factors influencing the technology adoption decisions by firms (e.g. Greer and Murtaza 2003) and large enterprises (e.g. Chang et al. 2003).

Work in the area of *Human Computer Interaction* (HCI) is user focused, involving both individuals and groups. Experiments and surveys are typical research methodologies. Prior IS works explore how personalization technologies interact with a user's cognitive style and characteristics, and influence user behaviors and perception (e.g. Kumar et al. 2004; Tam and Ho 2005). Focus groups and interviews are used to investigate why online users choose to personalize the appearance of their computers and cell phones (e.g. Blom and Monk 2003). Some HCI works address philosophical issues arising from personalization, including privacy ethics related to data collection (e.g. Awad and Krishnan 2006; Chellappa and Sin 2005). Though users demand more customized services, they are increasingly concerned about the threats to their privacy and how Internet firms use their data. This is not only a social science issue but also a concern for IS developers, because any restrictions on data collection will result in limitations on the Web mining process.

Our work aims at examining the effects of personalization strategies at the user level. That is, we adopt an HCI perspective, and drawing on literature in HCI and cognitive processing theories, our work investigates the effect of personalization on users' information processing.

Motivations and Research Questions

Debates on the Effectiveness of Personalization

Internet firms adopt personalization technology with the intention to better communicate with their users and to generate more business opportunities. Personalization can increase the value of an organization by focusing on customer intimacy. Nowadays, while personalization technology has become a crucial component of relationship management solutions, its effectiveness has yet to be proven.

Several authors have found evidence for the effective influence of personalization on users' decision-making (Kumar et al. 2004; Tam and Ho 2005), as well as for the perception of e-services (Nysveen and Pedersen 2004; Rust and Lemon 2001). By providing individualized content, offers, and services, personalization eliminates aimless surfing activities (Shahabi and Banaei-Kashani 2003) and eases business-to-consumer interaction (Ardissono et al. 2002). Also, personalizing Web content empowers Internet firms to deliver customer value and to achieve profitable growth (Greer and Murtaza 2003). It is reported that online retailers using personalization technology have significant revenue increases (Parkes 2001). One successful example is Levi Strauss. The firm adopted personalization technology to increase its cross-sell yield and found that its customers accept 76% of the recommended items (Cohan 2000 pp. 9).

On the other hand, there remains skepticism about the prospects for personalization. Several personalization initiatives have failed without generating any benefits to the adopting firms. One main reason for such failures is inappropriate resource allocation. Chellappa and Sin (2005) claim that investments in online personalization services may be severely undermined if online users do not use these services due to privacy concerns. On the side of users, a report by Jupiter Research (2003) indicates that only 14% thought that personalized recommendations on shopping Web sites lead the users to purchase more frequently. Nunes and Kambil (2001) conduct a survey and find that half of online users of numerous Web sites would rather customize a site themselves than have it automatically personalized for them.

Research Gaps

Why are there conflicting findings in personalization research? The authors identify three reasons that lead to these inconsistencies. First, most studies on personalization focus on one single system, and these systems use various strategies to personalize the content and are applied in different contexts. Their users have different needs, interests, knowledge, goals, and working tasks. This greatly reduces the generalizability of their findings.

Second, these studies use a variety of tasks and measurements to justify the effectiveness of personalization. For instance, in the study by Smyth and Cotter (2000), subjects are only asked to write down their perception of the personalization system in terms of content precision, ease of use, and speed of service. While the evaluation of each dimension is high, a more direct measure of effectiveness of personalization is to check whether the user actually accepts the recommended offerings.

Third, personalization research lacks any adequately developed theoretical basis. Researchers do not have a common ground for developing hypotheses and interpreting results. Thus, the lack of underlying theory leads to the current state of inconclusive results in the IS literature. The current trend in personalization research is on the information architecture and technical implementation of the systems (e.g. Cingil et al. 2000) and case analysis of individual system performance (e.g. Manber et al. 2000; Perkowitz and Etzioni 2000). Researchers have put little effort into building relatedness among studies.

Research Questions

To bridge these gaps, we take the view that personalization is driven by business objectives related to marketing promotion, and thereby can be considered as persuasive messages. In a sense, every user's click represents an opportunity of persuasion for the firms, and every user's download represents a successful outcome of a persuasion message.

This work addresses the research question: *What are the effects of different personalization strategies on users' information processing?* There are two issues that we are interested in. First, it would be very interesting to

understand how personalization affects the different stages of information processing within one single decision process. Second, we also explore whether the same effect persists when the user revisits the personalized Web site.

Following the above ideas, the research question is represented by the two sub-questions: (1) *How do different personalization strategies influence users' attention, elaboration, and decision-making?* (2) *Do users attend to personalized content and make decisions in their repeat visits?*

Our work addresses the above research questions by drawing on the extant literature on HCI theories and the Heuristic-Systematic Model (HSM) in cognitive psychology (Chaiken 1980; Griffin et al. 2002; Kang and Herr 2006; Meyers-Levy and Maheswaran 2004). Answers to these questions assist understanding the degree of reliance on personalization by new and repeat users. From a theoretical perspective, the results of this study contribute to the development of a more comprehensive theory of the effects of personalization on users' information processing and decision-making. It is also a pioneer work examining the effects of personalization in repeat visits. From a practical perspective, it provides Internet firms with knowledge of the effectiveness of personalization agents.

The structure of the paper is as follows: Sections 2 and 3 present the theoretical background and the hypotheses; two online studies are undertaken in Sections 4 and 5; Section 6 discusses the findings and Section 7 concludes the paper.

Theoretical Background

A Web site is a stimuli-based environment in which the stimuli take the form of text, images, audio, animations, or video. In a personalized environment, personalized messages are part of the stimuli. The design, format, modality, and timing of these personalized stimuli constitute various effects to influence a user. Before we discuss HSM in greater detail, it is useful to have a general understanding of human information processing in such a stimuli-based environment.

Human Information Processing

Humans process information in multiple stages. This approach consists of three main stages: *attention*, *elaboration*, and *decision* (Bargh 2002). At the attention stage, humans have to decide how to distribute their limited attention across a variety of stimuli. Humans generally are bombarded by information. This is particularly true in the Internet world. Advances in technologies have made the retrieval and distribution of information much easier. With limited cognitive capacity, humans cannot pay attention to all stimuli. Hence, they have to selectively allocate their cognitive capacity based on the auditory and visual salience of each stimulus. For example, a blinking text or an animated banner will attract humans' attention because it stands out from the background (Lim and Benbasat 2002; Zhang 2000).

Those stimuli detected will go through the attention stage and arrive at the elaboration stage. At this stage, it is often necessary for humans to allocate more cognitive capacity to processing stimuli. The oversupply of information on the Internet adds some stresses to human information processing. Humans may wrongly attend to useless stimuli, and, thus, they have to filter irrelevant and ambiguous data in order to locate the required information. Some stimuli being elaborated but found to be irrelevant may augment an existing memory schema without leading to a particular behavior.

At the decision stage, humans carefully process the messages and use various decision-making strategies to construct trade-offs and arrive at the final choice. Prior work shows that involvement, personal disposition, and contextual variables are factors affecting how humans process the stimuli in a biased way, and thus generate different decisions (Jain and Maheswaran 2000).

Heuristic Systematic Model

The Heuristic-Systematic Model (HSM) is an information processing model that describes how individuals reason a problem, form their judgments, and make their decisions (Griffin et al. 2002). HSM has two variables of interest: (a) which specific message elements drive the decision-making process, and (b) the nature of the cognitive processes the individuals go through. HSM proposes that when attempting to evaluate information in order to arrive at a judgment, the individuals use two different modes of cognitive processing that represent different levels of the depth

of thinking that the individuals devote to a communication. The high end corresponds to *systematic processing*, whereas the low end corresponds to *heuristic processing*.

Systematic processing is defined by effortful scrutiny and comparison of information. It has an analytic orientation in which an individual accesses and scrutinizes all of the accessible information relevant to the decision task. When the individuals' tendency to consider the focal topic is high, communication elements affect persuasion by acting as a relevant point of view. In this mode, the individual carefully considers message arguments to assess the logic, evidence, and validity. Diligent consideration of topic-relevant information is involved. Systematic processing mainly affects users' elaboration and decision.

On the other hand, heuristic processing takes place when only a subset of the accessible information is considered to complete the decision task. In other words, the individuals' predisposition to consider the focal topic is low. This mode is both less effortful and less capacity-limited. Usually individuals rely on the peripheral elements of messages to make a decision. Heuristic processing may affect all the three stages in information processing. Examples of peripheral elements include simple cues, such as the label of products, the strength of claims, or the length of product descriptions (Cline and Kellaris 1999). Cues are information that pertains to the essence of the arguments. They trigger the use of basic heuristics rules to complete the decision. For instance, a communication featuring a personalization source might convince the individuals by activating the heuristic rule, "personalized recommendations are trustful" (Zuckerman and Chaiken 1998).

The tendency to rely on systematic versus heuristic information in decision-making depends on numerous factors. Individuals are more likely to come up with their decisions based on heuristic processing when they have experiential motives (e.g. downloading a music file) than when they have instrumental motives (e.g. filing tax documents online). Since the motives vary across product categories, some categories of products (e.g. utilitarian products) are more likely to be processed systematically than other types of products (e.g. hedonic products). Moreover, other antecedents to the two processing modes include information adequacy, motivation, ability, time allowance, and self-efficacy (Chaiken 1980; Jain and Maheswaran 2000; Kang and Herr 2006).

Research Model and Hypotheses Development

In this study, the essence of personalization is captured by two variables: preference matching and the set size of personalized content. Taking an HSM approach, we group these variables into two categories that influence users in ways according to the systematic-heuristic dichotomy of HSM. Incorporating the three stages of information processing depicted in Section 2.1, we arrive at the following research model (Figure 1).

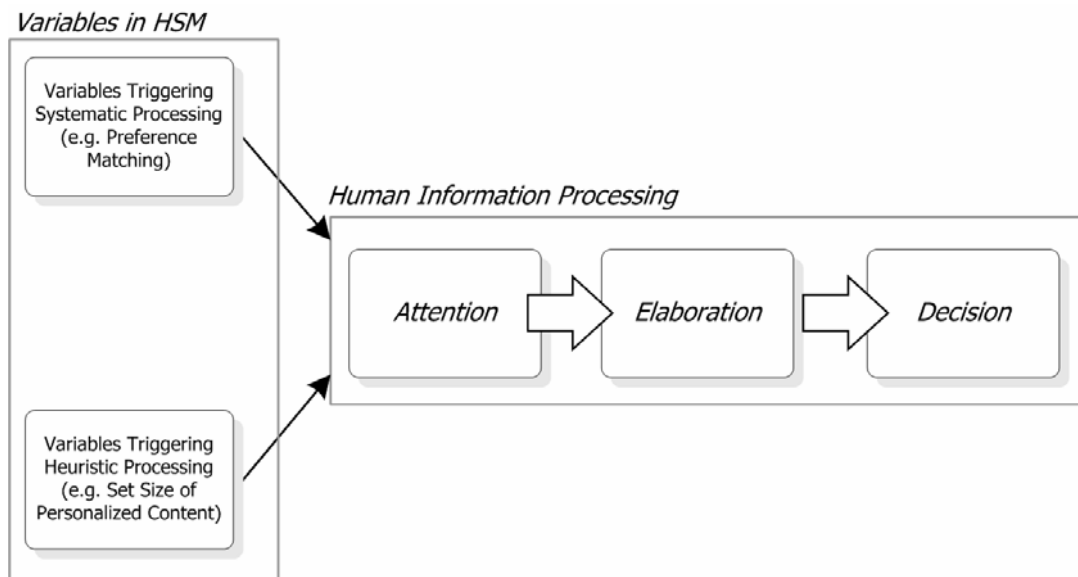


Figure 1. A Combined Model of HSM and Human Information Processing

Preference Matching of Personalized Content

HSM literature identifies the key variable that affects the persuasiveness of a message as being the quality of message arguments (Chaiken 1980). This variable leads to systematic processing. In the context of personalization, quality refers to the extent that the personalized content matches the need and preference of a user. We refer to it as *preference matching*. Personalized content that matches a user's preferences are more appealing to the user.

If a personalization agent is able to generate content that matches the tastes and preferences of the users, they are more likely to process the personalized content to a larger extent before arriving at a decision. That said, the users are found to predominantly seek information congruent to their preferences and to neglect conflicting information. Therefore, we anticipate that the success of personalization agents hinges on the ability of a Web site to understand and profile its users. However, *new* users to a Web site can judge whether the level of preference matching is high or low only after they have had a chance to assess the content. According to our model, preference matching is therefore insignificant at the attention stage. On the contrary, preference-matched content should increase elaboration. Thus, we hypothesize the following:

H1: If personalized content matches the preference of a user, then the user will elaborate much personalized content.

Since users have limited cognitive capacity (Wyer and Srull 1989), if they allocate considerable mental effort in processing personalized recommendations, they become less motivated to explore the remaining items (i.e., non-personalized items).

H2: If personalized content matches the preference of a user, then the user will elaborate less non-personalized content.

Following the view of HSM, argument quality has a direct effect on persuasion. If personalized content matches a user's preference, the user is more likely to be persuaded to take the personalized item. Therefore, we hypothesize the following:

H3: If personalized content matches the preference of a user, then the user is more likely to accept the personalized offer.

The role of preference matching switches from triggering the systematic processing mode to triggering the heuristic processing mode in users' repeat visits. If repeat users received high-quality personalized services in the previous visits, these users may have been impressed by the personalized content. Thus, "personalization" will become a cue attracting their attention in their repeat visits. Users will allocate more attention to personalized areas once they log on to the site. On the contrary, this cue may lose its influence if they find the cue to be misleading (Moore et al. 2003). Thus, we hypothesize the following:

H4: For a repeat user, if personalized content matches his preference in the previous visit, then it is more likely that the user will attend to personalized content in the next visit.

If users receive high-quality personalized content in the previous visits, they will develop a positive bias toward personalization. And "personalization" serves as a cue triggering heuristic processing. Also, content matching users' preference triggers systematic processing. Therefore, we propose the following:

H5: For a repeat user, if personalized content matches his preference in the previous visit, then the user is more likely to accept the personalized offer.

Set Size of Personalized Content

A fundamental question that Internet firms must address before developing a personalization strategy is how many offers should be provided to the users (Murthi and Sarkar 2003). In the real world, Internet firms vary in their strategy for determining the number of personalized recommendations. Some firms present a small number of recommendations. Barnes&Noble.com, for example, provides only two recommendations for each product category to new users and also provides a hyperlink, "More Recommendations", for each category. This reduces the cognitive loads of the users; however, the prior probability of the users to pick an item from a smaller set is lower. Some sites use the "fishing" approach, and tend to offer a large number of personalized offers. For instance, Amazon.com offers a lot of recommendations to its users. Though this increases the probability of being picked, customer

satisfaction is ruined if users consider this large number of offers/recommendations to be not personal. Our work refers the number of personalized offers as *set size of personalized content*.

Prior work suggests that the ability to capture users' attention depends on the saliency of the visual objects (Vecera and Farah 1994). Portions of the visual field to which users' attention is drawn are referred to as "visual saliency" (Taylor and Thompson 1982). After controlling for potential factors that may induce visual saliency (e.g. sharp color contrast, blinking objects), users are more likely to be attracted by a larger object. This is because the users' attentional resources are limited, and they tend to start exploring the information from a location that they can easily land on. Since a large set will provide a larger "landing strip" for the eyes, we propose the following hypothesis:

H6: It is more likely that a user attends to a large set of personalized content than to a small set of personalized content in the first visit.

From an information processing perspective, the users may judge a product based on its surface characteristics. These characteristics are conceived as an array of cues (Richardson et al. 1994). Examples of cues include colors of products, length of product description, and quantity of products. Cues mostly serve as heuristics in assessing the quality of a product (Price and Dawar 2002). Some users do not engage in a high degree of cognitive activity, and they simply assess these cues with few information searches.

The set size of personalized content is not expected to exert a direct effect on elaboration; that is, the level of elaboration will not grow with the number of recommended items. This is because people have a general belief that "items in a small amount are more valuable and luxurious". This is a schematic cue that they use to interpret personalized offers. If personalization agents only recommend a few offers, then people will consider those to be serious and valuable offers. We would argue that people like to explore more items from a small set. Therefore, if we take the set size into account and normalize the measurement of elaboration, then a small set is more effective than a large set. Hence, we hypothesize the following:

H7: If the set of personalized content is small, then a user will elaborate more personalized content (after normalization).

With a similar argument presented in the development of H2, users have limited cognitive capacity (Wyer and Srull 1989). If mental effort is allocated in processing personalized recommendations, then mental effort in processing non-personalized items will be outside the cognitive bounds. Thus, we hypothesize the following:

H8: If the set of personalized content is small, then a user will elaborate less non-personalized content (after normalization).

Following the view of HSM, the number of personalized recommendations has a direct effect on persuasion. Personalized offers from a small set are considered to be carefully generated by the agents. Thus, users are more likely to be persuaded to take the personalized item from a small set. Therefore, we hypothesize the following:

H9: It is more likely for a user to accept a personalized offer from a small personalized set than from a large personalized set (after normalization).

Is a small set still more effective than a large set when users revisit the Web site? They can more easily judge the quality of preference matching in a small set than in a large set, and, therefore, the set size can polarize the effects. Thus, we hypothesize the following:

H10: For a repeat user, there is an interaction effect between preference matching and set size of personalized content in the decision outcome with preference matching demonstrating a more salient effect on a small set than on a large set.

Figure 2 includes all hypotheses in our research model.

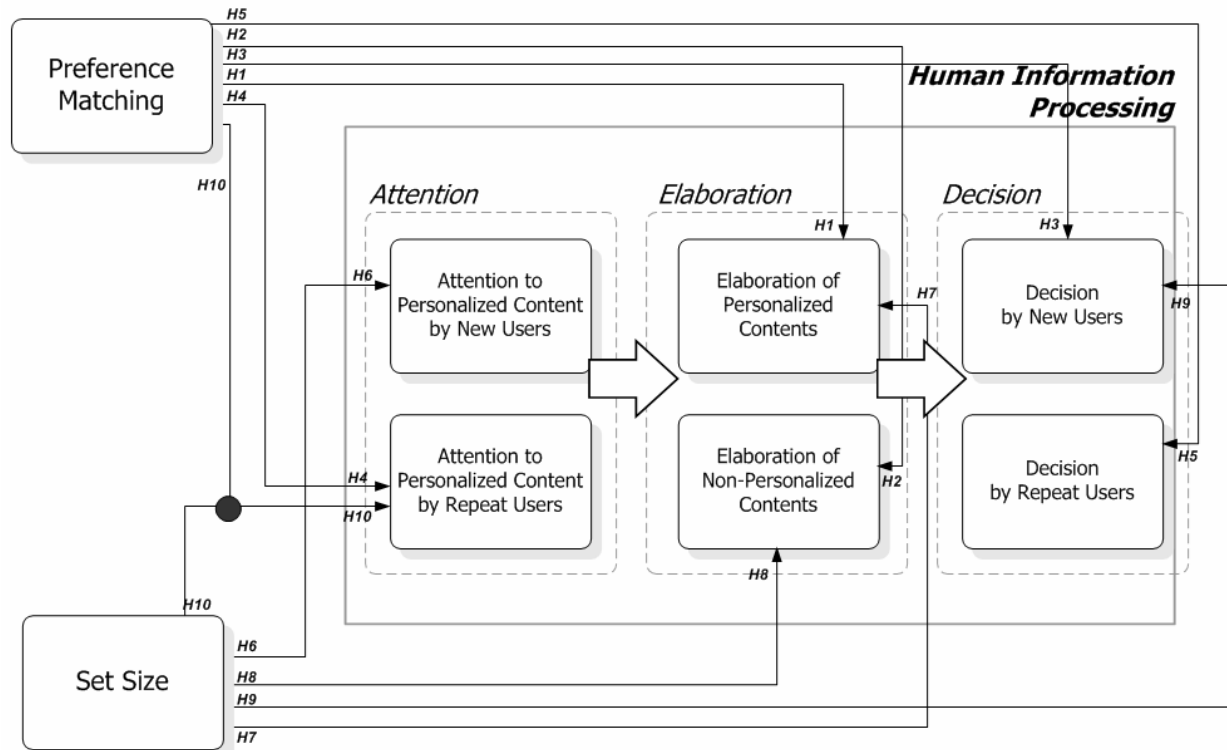


Figure 2. Research Model

Research Methodology

We conducted two field experiments to test the above hypotheses. In the first study, we cooperated with the largest mobile content provider in Hong Kong to develop a personalized ring tone Web site and invited its members to participate in the study. We examined the effect of personalization with a focus on comparing the effectiveness of a personalized offer list and a non-personalized alternative list. Effectiveness was measured in terms of the ability to capture the users' attention and influence their elaboration and decision. We controlled the numbers of items on the two lists. Findings of the first field experiment were augmented by the second field study. The second study involved a digital music download site. We cooperated with a digital music provider in Asia Pacific and developed a personalized music site. This self-developed site was highly similar to commercial Web sites, and it contained nearly 200,000 product items. Participants in the first study were invited to the personalized site once, whereas those in the second study were invited to the site repeatedly in a three-month period.

Study 1 – A Personalized Ring Tone Download Web site

An online field experiment in the context of a personalized ring tone download Web site was conducted to test the hypothesized relationships. The experimental design comprised two independent variables and four dependent variables. The independent variables were *preference matching* and *set size of personalized content*. The dependent variables were *attention*, *elaboration of the personalized and non-personalized lists*, and *decision outcome*.

Experimental Procedures

The mobile content provider sent 40,000 email invitations to its subscribers. Those who opted to participate in this study could click a link in the email to start the process. They could do the task at any time from any place.

The study was divided into three parts. First, the subjects were asked to fill in a questionnaire about their demographic information and ring tone download habit. Second, we asked the subjects to indicate their preferences for rhythms and artists. They chose and ranked their three favorite artists from a list of 18. We used the information from the Hong Kong Music Billboard to decide which tracks were popular from the artists' latest albums. Finally, all participants entered a Web page with twelve ring tone alternatives. The subjects could choose to download only one ring tone free of charge. After they confirmed to download a ring tone, the selected ring tone was sent to their mobile handsets via a short message service.

Design and Manipulation

The field experiment used a 2 x 2 full factorial design. The between-subject factors were preference matching and set size of personalized content.

(a) Preference Matching

To determine the list of ring tones for the experiment, we studied the transaction log provided by the mobile service provider to obtain a list of artists. This log contained the actual ring tone purchases of nearly 8,000 distinct users. There were more than 65,000 transactions in 16 months. These users downloaded ring tones from 175 distinct artists. We chose the top 18 artists, who accounted for 50% of the total number of download transactions. These transactions were conducted by 82% of the total number of distinct users. We then formed a pool of 72 ring tones from 18 artists (4 ring tones per artist). Most artists had two ring tones with fast rhythms, and the other two with slow rhythms. The ring tones in the same rhythm category were assigned a recommendation priority based on the information obtained from the Music Billboard.

There were two manipulation levels of preference matching: matched versus unmatched. Under the preference-matched condition, the personalized offers were generated based on the subject's previous transactions and preferences indicated in the questionnaires. Under the preference-unmatched condition, the offers were randomly generated. In both treatments, items on the non-personalized list were randomly extracted from the pool.

(b) Set Size of Personalized Content

There were two manipulation levels: a large set versus a small set. Under the large-set condition, the personalized list contained six ring tones, and the other list contained another six ring tones. Under the small-set condition, the personalized list contained three ring tones and the other list contained nine ring tones. That said, all subjects received a list of 12 ring tones from which to choose.

User Interface Design

Twelve ring tones were presented to a subject on a single page. Under a 1024 x 768 resolution, no page scrolling was needed for viewing the ring tones. There were two lists. The list on the right was "Personalized Recommendations", whereas the list on the left was "Other Offers" that listed non-personalized offers. The title of the track associated with each ring tone was used as a label, and the artist of the track was also indicated. All titles and artists were labeled in Chinese. For each ring tone, there were two buttons, one labeled as "Trial Listen" and the other as "Download". When the subject clicked the "Trial Listen" button, an audio file of the selected ring tone was streamed to the client machine. The subject could listen to the ring tone using Microsoft Media Player or Real Player. There was no restriction on the number of trial listenings. All mouse clicks were logged. When the subject clicked the "Download" button of a ring tone, the selected ring tone was sent to his/her mobile phone. There was no other hyperlink on the page. The interface is shown in Figure 3.

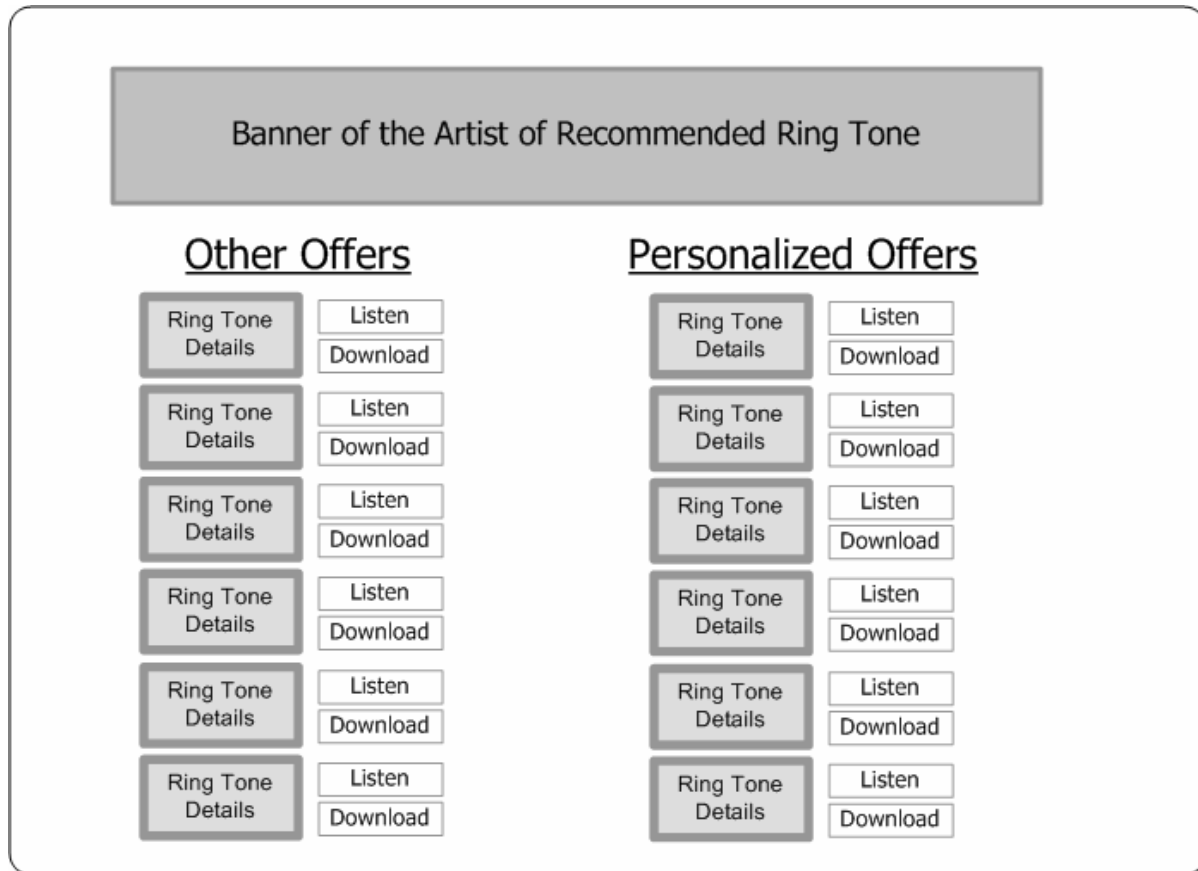


Figure 3. Web Interface for Study 1

Pretest

A pretest with 56 subjects was conducted to validate the instruments employed and to test the download system performance. The subjects confirmed that the navigation process and the selection task were smooth.

Dependent Variables

(a) Attention

Without an eyetracker, it was hard to accurately measure attention. In this study, we operationalized users' attention to be the first clicks once they logged on the site. This proxy has been used in prior HCI studies (e.g. Tam and Ho 2005).

(b) Elaboration

There were two measurements, elaboration of the personalized and non-personalized lists. The elaboration of personalized list was operationalized as the number of sampled ring tones on the personalized list. Since the numbers of ring tones shown on the personalized list were not the same under the large-set and small-set conditions, the prior probability of sampling a personalized ring tone was higher under the large-set condition. Thus, normalization was necessary for a fair comparison. As the number of personalized offers under the large-set condition doubled, we divided the counts of sampled, personalized ring tones by two.

The elaboration of non-personalized offers was operationalized as the number of sampled ring tones on the "Other Offers" list (i.e., non-personalized list). Similar to the above argument, there were nine (versus six) alternatives

shown on this list under the small-set (versus large-set) condition. The prior probability of sampling a ring tone from the “Other Offer” list was higher under the small-set condition. Thus, normalization was necessary for a fair comparison. We divided the counts of sampled, non-personalized ring tones by 1.5 under the small-set condition.

(c) Decision

At the end, all participants had to choose a ring tone from the given lists. The ring tone was sent to their mobile handsets via a short message service. The dependent variable was binary. A value of “1” represented that the choice was downloaded from the personalized list, whereas a value of “0” represented that the choice was downloaded from the non-personalized list.

Study 2– A Personalized Digital Music Download Web site

Study 1 controlled the ratios of non-personalized items to personalized items; the participants were invited to the Web site once only. To increase the external validity of our work, we conducted a second study that released the constraints of a balance between the personalized and non-personalized lists. The participants could visit the site multiple times within a 10-week time period. The second field experiment was in the context of a personalized digital music Web site. Similar to Study 1, Study 2 had two independent variables and four dependent variables, which will be explained in the following.

Experimental Procedures

The digital music content provider sent email invitations to its members and announced our study in its monthly newsletter. The participants could click a link in the emails to start the process.

First, they were asked to fill in a short questionnaire on their demographics and preferences for artists. They chose and ranked their three favorite artists from a list of 50 (32 Asian artists and 18 Western artists). After that, they were given four tokens for four free digital music files. They could enter our personalized Web site with 200,000 tracks, and sample any number of digital music files at any time. Every week, they could download only one track free of charge. After they confirmed to download a track, the selected track was sent to their computers. Throughout the 10-week period, we regularly uploaded new releases to the site. If the participants did not like the available tracks, they could keep the token and use it after we uploaded new tracks. That is, the participants were not “forced” to use the token. This greatly increased the external validity of this study.

Two pretests were conducted to test the download system performance. Thirty-five subjects were involved, and they could complete the whole process in 20 minutes.

Design and Manipulation

Similar to Study 1, the field experiment used a 2 × 2 full factorial design. The between-subject factors were preference matching and set size of personalized content.

(a) Preference Matching

There were two manipulation levels of preference matching: matched versus unmatched. Under the preference-matched condition, the personalized offers were matched to the subjects’ previous transactions and artist preferences indicated in the questionnaires. Under the preference-unmatched condition, the personalized offers were randomly extracted from the pool. Under both conditions, 200,000 tracks were available on the non-personalized lists. That said, the non-personalized lists in all groups were the same.

(b) Set Size of Personalized Content

There were two levels of manipulations: a large set versus a small set. Under the large-set condition, there were six personalized recommendations. Under the small-set condition, there were only three personalized recommendations. Differing from Study 1, the non-personalized lists were unchanged in all groups, and it contained nearly 200,000 tracks.

User Interface Design

There was a main menu on the left hand side, and a taxonomy listing six major groups of artists (i.e., local male/female/group artists, and international male/female/group artists). All personalized recommendations were shown at the bottom of the window. During the registration process, a subject could choose to display track titles and artists in Chinese or in English. For each track, there were three buttons: “Preview”, “Add to Basket” and “Evaluate”. When the subject clicked the “Preview” button, an audio file was streamed to the client machine. There was no restriction on the number of trial listenings. The subject could pick any number of favorite tracks and add them to the basket, and choose to evaluate a track in a 9-point Likert scale. After the subject clicked the “Logout” button, the tracks inside the basket would be shown. The subject had to pick one of them as the final choice. The music file in the *.wma format was then transferred to the client computer. The interface is shown in Figure 4.

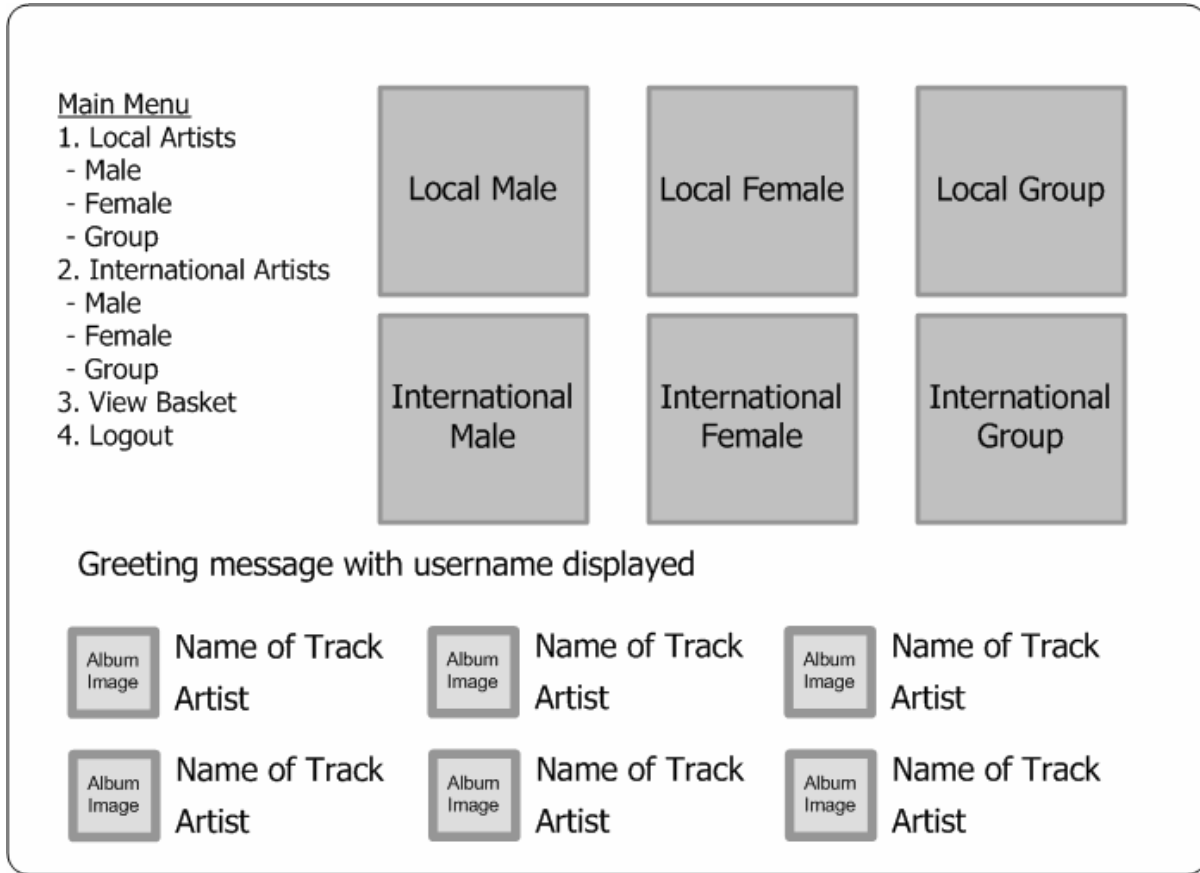


Figure 4. Web Interface for Study 2

Dependent Variables

Similar to Study 1, there were four dependent variables. They were attention, elaboration of the personalized and non-personalized lists, and decision outcome. The measurements of the dependent variables in Study 2 were identical to those in Study 1, except that the numbers of sampled, non-personalized tracks would not be normalized in Study 2, because the numbers of non-personalized alternatives were the same in all groups.

Data Analysis

Subjects

We summarize the demographics of the subjects in the two studies in Table 1. The following two subsections present the findings for Study 1 and Study 2 respectively.

Table 1. Descriptions of the Field Experiments

	Study 1	Study 2
Industrial Partner		
Name	Qlala.com:	EolAsia.com
Description	It is a major mobile content provider in Hong Kong, and it has 40,000 members.	It is a major digital music provider in Asia Pacific, and it has 50,000 members.
URL	http://www.qlala.com.hk	http://www.eolasia.com
Arrangements		
Study Period	6 weeks (from Nov 2003 to Jan 2004)	10 weeks (from Feb 2006 to Apr 2006) ¹
Tokens of Appreciation	1 Free Ring Tone + Lucky Draw	4 Free Music Files + Lucky Draw
No. of Free Downloads	1 Download	4 Downloads
No. of Rounds	1 Round	Unlimited
Participants		
Response Rate	8.17%	7.11%
No. of Data Points Used	516	416
Reasons for Discarding Some Data Points	The remaining data points are for other studies.	Only 416 participants completed at least two visits before April 30 2006.
Age	24.33	29.01
Gender	231 females and 285 males	202 females and 214 males

¹ Study 2 is still on-going at the time of paper submission.

Study 1 – A Personalized Ring Tone Download Web site

Table 2 summarizes the descriptive statistics for the dependent variables.

Table 2. Descriptive Statistics in Study 1

Attention	Preference Matching ($p < 0.01$)	49% (matched)	43% (unmatched)
	Set Size ($p < 0.01$) [H6]	60% (large)	29% (small)
	Interaction ($p > 0.1$)	25% (large, unmatched)	30% (small, unmatched)
		66% (large, matched)	49% (small, matched)
Elaboration of Personalized Offers	Preference Matching ($p < 0.01$) [H1]	2.99 (matched)	2.65 (unmatched)
	Set Size ($p > 0.1$) [H7]	2.87 (small) [un]	5.58 (large) [un]
		2.87 (small) [n]	2.79 (large) [n]
	Interaction ($p > 0.1$)	5.78 (large, matched) [un]	5.32 (large, unmatched) [un]
		3.11 (small, matched) [un]	2.64 (small, unmatched) [un]
		2.89 (large, matched) [n]	2.66 (large, unmatched) [n]
		3.11 (small, matched) [n]	2.64 (small, unmatched) [n]
Elaboration of Other Offers	Preference Matching ($p < 0.01$) [H2]	3.84 (matched)	3.24 (unmatched)
	Set Size ($p < 0.01$) [H8]	3.66 (small) [un]	3.48 (large) [un]
		2.44 (small) [n]	3.48 (large) [n]
	Interaction ($p < 0.05$)	3.90 (large, matched) [un]	3.04 (large, unmatched) [un]
		3.79 (small, matched) [un]	3.48 (small, unmatched) [un]
		3.90 (large, matched) [n]	3.04 (large, unmatched) [n]
		2.53 (small, matched) [n]	2.31 (small, unmatched) [n]
Choice	Preference Matching ($p < 0.01$) [H3]	52% (matched)	27% (unmatched)
	Set Size ($p < 0.1$) [H9]	47% (large)	33% (small)
	Interaction ($p > 0.1$)	33% (large, unmatched)	19% (small, unmatched)
		61% (large, matched)	43% (small, matched)

Note: [un] = before normalization; [n] = after normalization.

Attention

A logistic regression was conducted, with preference matching and set size of personalized content as the explanatory variables. According to Table 2, when the subjects had a large set to choose from, 60% of them first clicked the Personalized Offers, while only 29% of them first clicked the Personalized Offers when they had a small set to choose from. As hypothesized, the number of personalized offers had a main effect on attracting attention ($\chi^2(1)=7.68, p < 0.01$), supporting H6.

Elaboration

We first focused on the elaboration of personalized offers. Two-way ANOVA was conducted. Consistent with H1, the subjects were willing to expend effort in considering preference matching personalized offers (mean=2.99) but not random recommendations (mean=2.65) ($F(1,512)=13.63, p < 0.01$). Contrary to H7, the set size was not a significant factor affecting the elaboration of personalized offers. The subjects under the small-set condition sampled 2.87 ring tones, and those under the large-set condition sampled 2.79 (after normalization) ring tones ($F(1,512)=0.63, p > 0.1$).

We then examined the elaboration of non-personalized offers. Although both H2 and H8 showed significant results, the results were opposite of what we predicted. For H2, on average, the subjects sampled more non-personalized offers under the preference-matched condition (mean=3.84) than under the preference-unmatched condition (mean=3.24). There was a significant difference ($F(1,512)=65.77, p<0.01$). Moreover, for H8, there was a significant difference in the elaboration of non-personalized alternatives under the large-set and small-set conditions ($F(1,512)=12.51, p<0.01$). The normalized mean was 3.48 (versus 2.44) under the large-set (versus small-set) condition.

Decision

The results of a logistic regression revealed that ring tones matching a participant's preferences (52%) were downloaded more often than random offers (27%), supporting H3 ($\chi^2(1)=12.15, p<0.01$). Moreover, there was no significant main effect of set size on choice outcome. It is contrary to H9 ($\chi^2(1)=2.96, p<0.1$).

Study 2 – A Personalized Digital Music Download Web site

Table 3 summarizes the descriptive statistics for the dependent variables.

Table 3. Descriptive Statistics in Study 2

Attention (First Visit)	Preference Matching ($p>0.1$)	10% (matched)	13% (unmatched)
	Set Size ($p<0.01$) [H6]	16% (large)	7% (small)
	Interaction ($p>0.1$)	18% (large, unmatched)	7% (small, unmatched)
		12% (large, matched)	8% (small, matched)
Attention (Repeat Visit)	Preference Matching ($p<0.05$) [H4]	13% (matched)	11% (unmatched)
	Set Size ($p>0.1$)	14% (large)	9% (small)
	Interaction ($p<0.01$)	19% (large, unmatched)	9% (small, unmatched)
		11% (large, matched)	8% (small, matched)
Elaboration of Personalized Offers	Preference Matching ($p<0.01$) [H1]	2.93 (matched)	2.77 (unmatched)
	Set Size ($p<0.01$) [H7]	2.78 (large) [un]	2.89 (small) [un]
		1.39 (large) [n]	2.89 (small) [n]
	Interaction ($p<0.01$)	2.88 (large, matched) [un]	2.70 (large, unmatched) [un]
		3.00 (small, matched) [un]	2.83 (small, unmatched) [un]
		1.44 (large, matched) [n]	1.35 (large, unmatched) [n]
		3.00 (small, matched) [n]	2.83 (small, unmatched) [n]
Elaboration of Other Offers	Preference Matching ($p>0.1$) [H2]	6.40 (matched)	5.73 (unmatched)
	Set Size ($p>0.1$) ² [H8]	5.96 (small)	6.03 (large)
	Interaction ($p>0.1$)	6.40 (large, matched)	5.61 (large, unmatched)
		6.41 (small, matched)	5.84 (small, unmatched)

Note: [un] = before normalization; [n] = after normalization.

² As mentioned on page 13, the elaboration of non-personalized list was not normalized, because the numbers of items in both large-set and small-set conditions were the same.

Table 3. Descriptive Statistics in Study 2 (Cont.)

Choice (First Visit)	Preference Matching ($p < 0.01$) [H3]	18% (matched)	9% (unmatched)
	Set Size ($p > 0.1$) [H9]	11% (large)	15% (small)
	Interaction ($p > 0.1$)	8% (large, unmatched)	9% (small, unmatched)
14% (large, matched)		25% (small, matched)	
Choice (Repeat Visit)	Preference Matching ($p < 0.05$) [H5]	15% (matched)	11% (unmatched)
	Set Size ($p > 0.1$)	14% (large)	13% (small)
	Interaction ($p < 0.01$) [H10]	16% (large, unmatched)	3% (small, unmatched)
		11% (large, matched)	18% (small, matched)

Note: [un] = before normalization; [n] = after normalization.

Attention (First Visit)

A logistic regression was conducted, with preference matching and set size of personalized content as the explanatory variables. According to Table 3, 16% (versus 7%) of the subjects first clicked the personalized offers from a large (versus small) set. As hypothesized, the number of personalized offers had a main effect on attracting attention ($\chi^2(1)=7.38, p < 0.01$), supporting H6.

Attention (Repeat Visit)

H4 was tested in this study, because only subjects in Study 2 were invited to the site in multiple rounds. Table 3 shows that there was a significant difference in the means of the first clicks by the subjects who had received offers matched to (mean=13%) and not matched to (mean=11%) their preferences in the previous visit, supporting H4 ($\chi^2(1)=5.00, p < 0.05$).

Elaboration

We first examined the elaboration of personalized offers. Consistent with H1, the subjects were willing to expend effort in considering the offers matched to their preferences (mean=2.93), but not the random offers (mean=2.77) ($F(1,412)=54.34, p < 0.01$). The set size was a significant factor affecting the elaboration of personalized offers ($F(1,412)=130.33, p < 0.01$), supporting H7. The subjects under the small-set (versus large-set) condition sampled 2.89 (versus 1.39) tracks after normalization.

We then focused on the other alternatives. In Study 2, there were nearly 200,000 non-personalized tracks available. There were no significant effects from preference matching ($F(1,412)=0.40, p > 0.1$) (H2), the set size ($F(1,412)=0.01, p > 0.1$) (H8), and the interaction ($F(1,412)=1.37, p > 0.1$) on the elaboration of other alternatives. Thus, H2 and H8 were not supported.

Decision (First Visit)

The results of a logistic regression showed that there was a significant difference in the digital music downloads between preference-matched (18%) and preference-unmatched (9%) conditions. H3 was supported ($\chi^2(1)=7.93, p < 0.01$). And there was no significant main effect of the set size of personalized content on choice outcome. Eleven percent (versus 15%) of the subjects' downloads were from personalized list under the large-set (versus small-set) condition. This was contrary to H9 ($\chi^2(1)=0.10, p > 0.1$).

Decision (Repeat Visit)

The hypotheses (H5 and H10) that related to the decision outcome in repeat visits were tested in Study 2 only. Fifteen percent of the subjects who received digital music matched to the preferences would download a file on the personalized list in the return visit, whereas only 11% of those who received digital music not matched to their

preferences would download a personalized recommendation in the return visit. That said, the subjects had a higher tendency to download music files shown on the personalized list if they received a good recommendation previously. This supported H5 ($\chi^2(1)=6.38, p<0.05$). There was a strong interaction effect between the two independent variables ($\chi^2(1)=7.17, p<0.01$), supporting H10. Subjects under the small-set condition could distinguish content matched to their preferences from randomized content more easily.

Discussion

This work investigates the impact of personalization on user behavior, building on the extant work in consumer decision research, and indicates that personalization affects the processing of Web stimuli and decision outcomes. The use of Heuristic-Systematic Model allows us to study the effects of different personalization strategies on different stages of users' decision-making.

Major findings are summarized in Table 4 and are discussed below.

Table 4. Summary of Hypotheses

Hypotheses	Study 1	Study 2
H1: If personalized content matches the preference of a user, then the user will elaborate much personalized content.	p<0.01	p<0.01
H2: If personalized content matches the preference of a user, then the user will elaborate less non-personalized content.	p<0.01+	p>0.1
H3: If personalized content matches the preference of a user, then the user is more likely to accept the personalized offer.	p<0.01	p<0.01
H4: For a repeat user, if personalized content matches his preference in the previous visit, then it is more likely that the user will attend to personalized content in the next visit.	N/A	p<0.05
H5: For a repeat user, if personalized content matches his preference in the previous visit, then the user is more likely to accept the personalized offer.	N/A	p<0.05
H6: It is more likely that a user attends to a large set of personalized content than to a small set of personalized content in the first visit.	p<0.01	p<0.01
H7: If the set of personalized content is small, then a user will elaborate more personalized content (after normalization).	p>0.1	p<0.01
H8: If the set of personalized content is small, then a user will elaborate less non-personalized content (after normalization).	p<0.01+	p>0.1
H9: It is more likely for a user to accept a personalized offer from a small personalized set than from a large personalized set (after normalization).	p<0.1	p>0.1
H10: For a repeat user, there is an interaction effect between preference matching and set size of personalized content in the decision outcome with preference matching demonstrating a more salient effect on a small set than on a large set.	N/A	p<0.01

Note: + = the direction is opposite to what we predict.

To address the first research question, “*How do different personalization strategies influence users' attention, elaboration and decision-making?*”, we conceptualize the widely practiced personalization strategies in the industry into two variables in the model: preference matching and set size of personalized content. The first variable measures the extent to which Web content is matched to the users' preferences, while the second variable measures the extent to which Internet firms use personalized content to complement or supplement general content. For firms that are unable to invest in expensive personalization software, the current work suggests that heuristics variables can also exert an effect on users' attention. For example, the set size of personalized content has a salient effect on

attracting users' attention. As hypothesized, a large set diverts the attention of users (H6), and this is confirmed in both studies. This aligns with prior work. That is, the ability to draw attention depends on the saliency of the visual objects (Taylor and Thompson 1982; Van der Heijden 1992; Vecera and Farah 1994; Zhang 2000). The Internet provides rich information, and users' attention is a rare resource. This echoes the remark by Herbert Simon that "a wealth of information creates a poverty of attention". Our finding is useful for those Internet firms in structuring its personalization strategies to capture users' attention.

Our findings provides some evidence that after normalization, a small set is effective to affect users' elaboration (H7 in Study 2), and it can stimulate users to browse much non-personalized content (H8 in Study 1). This is contradictory to what we predict. However, we could not obtain significant findings for hypotheses H7 and H8 in both Study 1 and Study 2. This gives rooms to future research to investigate the underlying reasons.

Will users rely on personalization and ignore other offers? Our findings show that if there are a lot of personalized offers (H8) or personalized offers that do not fit the users' needs (H2), they have a tendency to seek additional information. This is particularly true if the amount of non-personalized content is not much (i.e., Study 1). Therefore, if Internet firms want to promote the personalized offers, they must ensure that the quality of personalized offers is high. If users find that personalized offers are not very good, they will lose confidence in personalization eventually.

We develop H4, H5 and H10 to address the second research question, "*Do users attend to personalized content and make decisions in their repeat visits?*". If users receive content matched to their preferences, a positive feeling is developed. Though personalized content cannot attract users' attention in the first visit, "personalization" becomes a cue to attract their attention in the following visits (H4). This aligns with the findings in other IS studies, which demonstrate the behaviors of new and repeat users are different (Zhang 2000). Our findings provide evidence that the role of preference matching switches from a variable leading to systematic processing to a variable leading to heuristic processing. The quality of personalized content does matter in influencing users' first (H1 and H3) and repeat (H4, H5 and H10) visits.

Conclusion and Limitations

This work draws on the extant literature on human information processing to conceptualize the impact of personalization on users' decision-making processes with two variables: preference matching and set size of personalized content. It also sheds light on the effectiveness of personalization to Internet firms in offering unique experiences to new and repeat users. Most of the hypotheses on the impact of personalization on cognitive processing, behavior and decision are supported based on two field studies. In sum, personalization could offer competitive advantages to Internet firms, as users generally are more willing to explore the personalized content further. Moreover, personalized communications have the potential to reduce information overload and provide aids to decision-making. More works need to be done to better understand the issues brought about by personalization.

References

- Adomavicius, G., and Tuzhilin, A. "Personalization Technologies: A Process-Oriented Perspective," *Communications of the ACM* (48:10), October 2005, pp.83-90.
- Ardissono, L., Goy, A., Petrone, G., and Segnan, M. "Personalization in Business-to-Customer Interaction," *Communications of the ACM* (45:5), 2002, pp.52-53.
- Awad, N.F., and Krishnan, M.D. "The Personalization Privacy Paradox: An Empirical Evaluation of Information Transparency and the Willingness to be Profiled Online for Personalization," *MIS Quarterly* (30:1), March 2006, pp.13-28.
- Banker, R.D., and Kauffman, R.J. "The Evolution of Research on Information Systems: A Fiftieth-Year Survey of the Literature in Management Science," *Management Science* (50:3), 2004, pp.281-298.
- Bargh, J.A. "Losing Consciousness: Automatic Influences on Consumer Judgment, Behavior, and Motivation," *Journal of Consumer Research* (29:2), 2002, pp.280-285.
- Blom, J.O., and Monk, A.F. "Theory of Personalization of Appearance: Why Users Personalize Their PCs and Mobile Phones," *Human-Computer Interaction* (18:3), 2003, pp.193-228.
- Chaiken, S. "Heuristic versus Systematic Information Processing in the Use of Source versus Message Cues in Persuasion," *Journal of Personality and Social Psychology* (39:5), November 1980, pp.752-766.

- Chang, K.C., Jackson, J., and Grover, V. "E-commerce and Corporate Strategy: An Executive Perspective," *Information & Management* (40:7), August 2003, pp.663-675.
- Chellappa, R.K., and Sin, R.G. "Personalization versus Privacy: An Empirical Examination of the Online Consumer's Dilemma," *Information Technology and Management* (6:2-3), April 2005, pp.181-202.
- Chiasson, T., Hawkey, K., McAllister, M., and Slonim, J. "An Architecture in Support of Universal Access to Electronic Commerce," *Information and Software Technology* (44:5), April 2002, pp.279-289.
- Cingil, I., Dogac, A., and Azgin, A. "A Broader Approach to Personalization," *Communications of the ACM* (43:8), 2000, pp.136-141.
- Cline, T.W., and Kellaris, J.J. "The Joint Impact of Humor and Argument Strength in a Print Advertising Context: A Case for Weaker Arguments," *Psychology and Marketing*. (16:1), 1999, pp.69-86.
- Cohan, P.S. *E-Profit: High-Payoff Strategies for Capturing the E-Commerce Edge*, AMACOM, 2000.
- Greer, T.H., and Murtaza, M.B. "Web Personalization: The Impact of Perceived Innovation Characteristics on the Intention to Use Personalization," *Journal of Computer Information Systems* (43:3), Spring 2003, pp.50-55.
- Griffin, R.J., Neuwirth, K., Giese, J., and Dunwoody, S. "Linking the Heuristic-Systematic Model and Depth of Processing," *Communication Research* (29:6), 2002, pp.705-734.
- Jain, S.P., and Maheswaran, D. "Motivated Reasoning: A Depth-of-Processing Perspective," *Journal of Consumer Research* (26:4), 2000, pp.358-371.
- Jupiter Research Reports That Web Site "Personalization" Does Not Always Provide Positive Results.* (October 14 2003). Retrieved November 30, 2005, from <http://www.jupitermedia.com/corporate/releases/03.10.14-newjupresearch.html>.
- Kang, Y.S., and Herr, P.M. "Beauty and the Beholder: Toward an Integrative Model of Communication Source Effects," *Journal of Consumer Research* (33:1), 2006, pp.123-130.
- Komiak, S.Y.X., and Benbasat, I. "The Effects of Personalization and Familiarity on Trust and Adoption of Recommendation Agents," *MIS Quarterly*, forthcoming.
- Kumar, R.L., Smith, M.A., and Bannerjee, S. "User Interface Features Influencing Overall Ease of Use and Personalization," *Information & Management* (41:3), January 2004, pp.289-302.
- Lim, K., and Benbasat, I. "The Influence of MultiMedia in Improving the Comprehension of Organizational Information," *Journal of Management Information Systems* (19:1), 2002, pp.99-127.
- Loia, V., Pedcrycz, W., Senatore, S., and Sessa, M.I. "Web Navigation Support by Means of Proximity-Driven Assistant Agents," *Journal of the American Society for Information Science and Technology* (57:4), February 2006, pp.515-527.
- Manber, U., Patel, A., and Robison, J. "Experience with Personalization on Yahoo!," *Communications of the ACM* (43:8), 2000, pp.35-39.
- Meyers-Levy, J., and Maheswaran, D. "Exploring Message Framing Outcomes When Systematic, Heuristic, or Both Types of Processing Occur," *Journal of Consumer Psychology* (14:1/2), 2004, pp.159-167.
- Moores, E., Laiti, L., and Chelazzi, L. "Associative Knowledge Controls Deployment of Visual Selective Attention," *Nature Neuroscience* (6:2), February 2003, pp.182-190.
- Murthi, B.P.S., and Sarkar, S. "The Role of the Management Sciences in Research on Personalization," *Management Science* (49:10), October 2003, pp.1344-1362.
- Nunes, P.F., and Kambil, A. "Personalization? No Thanks." *Harvard Business Review*. (79:4), April 2001, pp.32-33.
- Nysveen, H., and Pedersen, P.E. "An Exploratory Study of Customers' Perception of Company Web Sites Offering Various Interactive Applications: Moderating Effects of Customers' Internet Experience," *Decision Support Systems* (37:1), April 2004, pp.137-150.
- Pal, N., and Rangaswamy, A. *The Power of One: Gaining Business Value from Personalization Technologies*, Trafford, England, 2003.
- Perkowitz, M., and Etzioni, O. "Adaptive Web Sites," *Communications of the ACM* (43:8), 2000, pp.152-158.
- Poulin, M., Montreuil, B., and Martel, A. "Implications of Personalization Offers on Demand and Supply Network Design: A Case from the Golf Club Industry," *European Journal of Operational Research* (169:3), March 2006, pp.996-1009.
- Price, L. and Dawar, N. "The Joint Effects of Brands and Warranties on Signalling New Product Quality," *Journal of Economic Psychology* (23:2), 2002, pp.165-190.
- Richardson, P.S., Dick, A.S., and Jain, A.K. "Extrinsic and Intrinsic Cue Effects on Perceptions of Store Brand Quality," *Journal of Marketing* (58), 1994, pp.28-36.
- Rust, R.T., and Lemon K.N. "E-Service and the Customer," *Internal Journal of Electronic Commerce* (5:3), 2001, pp.85-101.

- Shahabi, C., and Banaei-Kashani, F. "Efficient and Anonymous Web-Usage Mining for Web Personalization," *Journal on Computing* (15:2), Spring 2003, pp.123-147.
- Smyth, B., and Cotter, P. "A Personalized Television Listings Service," *Communications of the ACM* (43:8), 2000, pp.107-111.
- Tam, K.Y., and Ho, S.Y. "Web Personalization as a Persuasion Strategy: An Elaboration Likelihood Model Perspective," *Information Systems Research* (16:3), September 2005, pp.271-293.
- Tam, K.Y., and Ho, S.Y. "Understanding the Impact of Web Personalization on User Information Processing and Decision Outcomes," *MIS Quarterly*, forthcoming.
- Taylor, S.E., and Thompson, S.C. "Stalking the Elusive 'Vividness' Effect," *Psychological Review* (89:2), 1982, pp.155-181.
- Van der Heijden, A.H.C. *Selective Attention in Vision*, Routledge, NY, 1992.
- Vecera, S.P., and Farah, M.J. "Does Visual Attention Select Objects or Locations?" *Journal of Experimental Psychology* (123:2), 1994, pp.146-160.
- Wyer, R. S., and Srull, T. K. *Memory and Cognition in its Social Context*, Lawrence Erlbaum Association, 1989.
- Xiao, B., and Benbasat, I. "E-Commerce Product Recommendation Agents: Use, Characteristics, and Impact," *MIS Quarterly*, forthcoming.
- Zhang, P.A. "The Effects of Animation on Information Seeking Performance on the World Wide Web: Securing Attention or Interfering with Primary Tasks?" *Journal of the Association for Information Systems* (1), 2000, pp.1-28.
- Zuckerman, A., and Chaiken, S. "A Heuristic-Systematic Processing Analysis of the Effectiveness of Product Warning Labels," *Psychology and Marketing* (15:7), 1998, pp.621-642.