Web Personalization as a Persuasion Strategy: An Elaboration Likelihood Model Perspective

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With advances in tracking and database technologies, firms are increasingly able to understand their customers and translate this understanding into products and services that appeal to them. Technologies such as collaborative filtering, data mining, and click-stream analysis enable firms to customize their offerings at the individual level. While there has been a lot of hype about web personalization recently, our understanding of its effectiveness is far from conclusive. Drawing on the elaboration likelihood model (ELM) literature, this research takes the view that the interaction between a firm and its customers is one of communicating a persuasive message to the customers driven by business objectives. In particular, we examine three major elements of a web personalization strategy: level of preference matching, recommendation set size, and sorting cue. These elements can be manipulated by a firm in implementing its personalization strategy. This research also investigates a personal disposition, need for cognition, which plays a role in assessing the effectiveness of web personalization. Research hypotheses are tested using 1,000 subjects in three field experiments based on a ring-tone download website. Our findings indicate the saliency of these variables in different stages of the persuasion process. Theoretical and practical implications of the findings are discussed.

Key words: web personalization; elaboration likelihood model; persuasion; preference matching; human computer interaction; recommendation set size; sorting cue

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1. Introduction

Advanced information technologies such as collaborative filtering, data mining, and click-stream analysis enable firms to customize their offerings at the individual level. Increasingly, users of web services are experiencing interactions with service providers that are not only unique, but are also more enjoyable and effective than those through a one-size-fits-all approach (Rust and Lemon 2001). One-to-one marketing and personalized offerings are made possible through the deployment of technologies1 that perform real-time tracking, data mining, and dynamic content generation. These technologies empower firms to induce customers to attend to web content (e.g., banner ads) or behave in ways (e.g., purchase) that are congruent with the firm’s objective (e.g., cross-selling). The result is a new mode of interaction between a firm and its customers that is generally referred to as web personalization. Broadly speaking, web personalization leverages personalization technologies to provide the right content in the right format to the right person at the right time. The objective is to provide customized services and to maximize business opportunities. It is expected that corporate investment in personalization technologies will continue to surge in the future (Kim et al. 2001, Ledford 2002, Rust and Lemon 2001).

While there has been a lot of hype about web personalization recently, our understanding of its

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1 For the rest of the paper, these technologies are called personalization agents.
effectiveness is far from conclusive. Advocates of web personalization point out that personalization agents have changed the web into a personal communication medium. By providing individualized content, offerings, and services, web personalization helps to control aimless surfing activity (Light and Maybury 2002) and to facilitate business-to-consumer interaction (Ardisono et al. 2002). Also, personalizing web content empowers firms to deliver customer value and to achieve profitable growth (Allen et al. 1998, Peppers and Rogers 1997). It has been reported that e-commerce websites using personalization technology have seen annual revenue increases of up to 52% (Parkes 2001). One successful example is Levi Strauss. The firm adopted personalization technology to increase its cross-sell yield and found that its customers accepted 76% of the recommended items (Cohan 2000, p. 9).

On the other hand, skepticism about the prospects of web personalization remains. Festa (2003) remarked that firms seeking to personalize their websites in the hope of boosting online sales are not getting the expected payback. It costs about four times as much to personalize a website than to run a comparable adaptive site. According to Jupiter Research (2003), only 14% of users think that personalized offers or recommendations on shopping websites lead them to purchase more frequently.

Given the proliferation of web personalization, it is surprising to find that there is little behavioral research on the topic so far. While related work in economics and product customization has been surveyed by Murthi and Sarkar (2003), these studies are analytical in nature. The authors remarked that “we found no research on empirical validation of the assumptions or the results of analytical models providing substantial opportunities for researchers” (p. 1,350). So far, few studies have investigated the mechanism by which personalized content influences the decision process of web users.

The objective of the current research is to enhance our understanding of web personalization and its effectiveness as a communication channel. We take the view that the interaction between a personalized web agent and a user is one of communicating a persuasive message to the user driven by business objectives. In particular, we are interested in the following research questions: (1) What are the effects of different personalization strategies at different stages in the process of persuasion? (2) What are the variables related to the user’s personal disposition and technology features that may have an impact on each stage of the process? Answers to these two questions will help us to delineate the effects of web personalization on different stages of persuasion and highlight the role and effectiveness of technology features at each stage.

For this research, we cooperated with a mobile content provider to conduct a number of field experiments. Participants were recruited to download ring tones for their mobile handsets from a personalized website. The collected data were used to empirically examine the persuasiveness of web personalization.

The remainder of this paper is organized as follows. In the next section, we introduce the elaboration likelihood model (ELM) as the theoretical frame of the current work. The ELM was originally developed to understand the processing of persuasive messages from a social psychology perspective. We adopted the ELM to guide our investigation of the relationships between web personalization, personal disposition, elaboration, and decision outcome. Section 3 presents the research questions and the hypotheses derived from the model. This is followed by an overview of three ring-tone studies in §§4 and 5. Section 6 discusses the findings and their theoretical and practical implications. Section 7 concludes the paper.

2. The Elaboration Likelihood Model of Persuasion
A website can be conceptualized as a stimuli-based decision-making environment. The stimuli take the form of text, images, audio, animations, or video. In the context of web personalization, the design, format, modality, and timing of these stimuli constitute different persuasive efforts to influence a user. Personalized content is driven by business objectives related to market promotion, cross-selling, and up-selling.2 and

Cross-selling involves persuading a customer to consider buying a complementary product, such as selling car insurance after a car sale; up-selling involves persuading a customer to buy a more expensive or upgraded line of product.
therefore can be considered as persuasive messages.\textsuperscript{3}
In a sense, every page click represents a persuasion opportunity for a firm.

In the course of interacting with a website, these persuasive messages influence a user by diverting attention, reallocating cognitive resources, and evoking affective responses and behaviors. The extent to which a firm can leverage personalization technologies to construct a persuasive message with the right attributes (i.e., content, modality, frequency), and to deliver it effectively to the right person at the right time, has salient effects on the outcome of the firm’s communication strategy.

The effectiveness of web personalization is framed in the context of persuasion. As such, the questions become: (1) How is the persuasion process induced by web personalization characterized, and (2) what are the factors that facilitate the persuasion process and what is their relative saliency in each stage of the process? To provide a theoretical frame for our analysis, we make reference to the elaboration likelihood model of persuasion (ELM) ( Petty and Cacioppo 1986b). Originally, the model was developed to provide an organized framework to address issues related to information sources, personality, and context effects of persuasion (Areni et al. 2000). It stipulates a process rather than a variable approach to persuasion. By doing so, it allows the same variable to induce different behaviors at different stages of the persuasion process. The ELM has made it possible to explain the mixed results of previous studies using a single theoretical framework.

2.1. Stages of Information Processing and Level of Cognitive Effort

Before we discuss the ELM in greater detail, it would be useful to understand how humans process information. Here, we focus on two dimensions of information processing: the process and the level of cognitive effort. A typical information-processing model postulates a stage approach consisting of the following stages: attention, elaboration, and behavior (Bargh 2002). While the stage approach depicts the complete process of message processing, not every message detected will go through all the stages. Some messages may augment/change an existing memory schema without leading to a particular behavior. Some may not even get the attention of the person. It thus becomes important to understand how web personalization affects each stage of information processing.

The other dimension of information processing is the level of cognitive effort on the receiver side. According to MacInnis and Jaworski (1989), there are six levels of information processing. If the attention of users is very low, stimuli are immediately analyzed and yield few or no effects (Greenwald and Leavitt 1984). This is named the preattention stage. At the next level of information processing, the attention is focal; it is divided between the message and a secondary task. Users transfer their attention from the secondary task to the personalized message (e.g., personalized banners on the web), a process that resembles classical conditioning. At the third level, when the motivation to process information is low to moderate, users direct their attention toward the message; however, the cognitive capacity remains low and they use easy-to-process cues in order to make a heuristic assessment of the message. At the fourth level, users are moderately motivated and try to integrate the full information of the message. They use their prior knowledge and experience, which leads to central processing of the message (MacInnis and Jaworski 1989). At the fifth level, users are involved; that is, they relate their own experience to the message. At the sixth and deepest level, users embellish the message information, adding either positive or negative attributes and uses not mentioned in the message (Mick 1992). The different stages of information processing and the various levels of cognitive effort are summarized in Figure 1. The figure consists of three stages, with Levels 1–2 mapped to the attention stage and Levels 3–6 mapped to the elaboration stage. As message processing is central to persuasion, we expect that the process of persuasion will follow that of information processing, as outlined here.

2.2. The Elaboration Likelihood Model

The original ELM is depicted in Figure 2. It focuses on the second stage of information processing.
As mentioned earlier, the ELM embraces a “process-oriented” approach, rather than a “variable-oriented” approach to persuasion (Dillard and Pfau 2002). The model suggests that a person has a continuum of elaboration approaches to process persuasive messages. Users may engage in elaborating issue-relevant thinking or they may use simple decision rules to respond to these messages. The nature of elaborative processing goes beyond simply paying attention to or comprehending the arguments in the message. Elaborative processing involves generating one’s own thoughts in response to the information to which one is exposed.

When message recipients have both the motivation and the ability to consider detailed information in a given message, persuasion occurs via the central route. This route is taken when information processing is based upon critical thinking and the message is given due consideration. Central processing requires more cognitive effort than does peripheral processing. The recipient scrutinizes all available information relevant to the message. Any attitude change is
driven by the careful consideration of, and idiosyncratic responses to, relevant arguments supporting the advocated position.

When message recipients lack either the motivation or the ability to process the detailed information in the message content, they engage in peripheral processing. They rely on simple cues (e.g., “This is a personalized product for me, so it should be good.”) for judgment formation. The peripheral route is taken. The recipients undertake less thoughtful processing. Only part of the information is processed and inferences based on rules of thumb are used to make the decision. For peripheral processing to take place, an associated decision rule has to be cognitively available, accessible, and perceived as a reliable basis for judgment (Eagly and Chaiken 1993). For instance, a recipient may form a more favorable attitude toward the message when a promotion e-mail is addressed to him/her personally (e.g., addressing the recipient using his/her first name) than when a generic message is received. In this example, the recipient may invoke a rule that “personalized recommendations are tailored for me and therefore can be trusted” and his/her subsequent attitude conforms to the message’s advocacy. The central questions for a firm deploying personalization agents are whether these heuristic rules exist and how to trigger them in a web environment.

3. Research Model and Hypotheses
By combining the information-processing model and the ELM, we obtain our research model, as depicted in Figure 3. The essence of personalization is captured by three variables: level of preference matching, sorting cue, and recommendation set size. They are grouped into two categories and influence users in ways according to the central-peripheral dichotomy of the ELM. Given our focus on the behavioral outcomes induced by personalized web content, attitude is not included in the model.

3.1. Preference Matching—Central Route of Persuasion
The ELM literature identifies the major variable that affects the persuasiveness of a message as the quality/merits of the message’s arguments. This variable is found to affect elaboration through the central route of persuasion. In the current context, preference matching is selected as the variable affecting elaboration through the central route. The level of preference
matching refers to the extent to which the web content generated by the personalization agent appeals to users. If a personalization agent is able to generate content that matches the taste and preference of a user, the user is more likely to process the content (e.g., personalized offers) to a larger extent before arriving at a decision (e.g., accept the offers). It is important to note that the ELM does not specify that an adequately elaborated message necessarily leads to a favorable outcome. It only indicates that the arguments associated with a message will be scrutinized through an elaboration process, the extent of which is determined by the presence (or absence) of a number of persuasion factors. Having said that, a heightened level of elaboration does have a positive impact on a firm’s promotion strategy, as the message is more likely to sink into the user’s long-term memory.

The success of web personalization hinges on the ability of a website to understand and profile its users. One measure of the quality of web personalization is the extent to which offerings generated by the personalization agent match the preferences of the user in a particular domain. However, whether the level of preference matching is high or low can only be judged after the user has a chance to evaluate the content. According to our model, preference matching is therefore irrelevant at the attention stage. On the other hand, preference-matching content should heighten elaboration because the content consists of items that match the user’s preferences. Thus, we hypothesize the following.

**HYPOTHESIS 1 (H1).** Content with a high level of preference matching leads to more elaboration than does content with a low level of preference matching.

Following the tenets of the ELM, argument quality/merit has a direct effect on persuasion. If the personalized content matches the user’s preference, a user is more likely to be persuaded to accept the recommended item. Therefore, we hypothesize the following.

**HYPOTHESIS 2 (H2).** The decision to accept a personalized offer is more likely with a high level of preference matching than with a low level of preference matching.

### 3.2. Sorting Cues and Recommendation Set Size—Peripheral Route of Persuasion

A personalization agent is equipped with tools to dynamically structure the format of its web content and to provide sorting cues to guide users in their decision-making process. For example, websites often arrange options (e.g., product search results) in the form of a list with the first entry representing the most desired option. Using the terminology of the ELM, these strategies correspond to information processing via the *peripheral route* by triggering users’ heuristic rules.

These strategies, in essence, do not change the quality of the content itself (i.e., the level of preference matching) or improve/degrade the ability of the agent to offer preference-matching content to users. However, their effects become salient when users have a weak motivation or ability to process the persuasive message. Variables that exert their influence in this way are said to take the peripheral route. In the current research, we focus on two peripheral variables: a sorting cue and recommendation set size.

#### 3.2.1. Sorting Cue

Increasingly, websites use sorting cues to direct users’ click behaviors. For instance, Amazon.com invites readers to evaluate products and calculates the average customer rating of each product. Other users can then use this score as a reference for making purchase decisions. Also, each product has an indicator, *Amazon.com Sales Rank*, to indicate the popularity of the product. When a person clicks on the link to his/her personal bookstore managed by Amazon.com, he/she can view a list of book recommendations. The order of recommended items is an example of a sorting cue. As with search engines, users tend to browse through only the first few items on a long list of search results (Eastman 2002). Items high up on the list are accessed more often than those further down the list. In line with previous research, therefore, we hypothesize the following.

**HYPOTHESIS 3 (H3).** Content with a sorting cue is more likely to attract attention than content without a sorting cue.

As a peripheral variable, a sorting cue triggers users’ heuristic rules to process the web content. Very often, cued personal offers are labeled as “personalized offers,” “your recommendations,” and so forth.
Previous work in psychology has indicated that self-referent messages have salutary effects on recall and elaboration (Ferguson et al. 1983, Klein and Kihlstrom 1986, Klein and Loftus 1988, Rogers et al. 1977). Following this line of reasoning, a sorting cue is expected to exert a direct effect on elaboration, as stated in the following hypothesis.

**Hypothesis 4 (H4).** Content with a sorting cue is more likely to induce elaboration than content without a sorting cue.

According to Petty and Cacioppo (1986a), peripheral persuasion variables may affect the extent or direction of message processing. In other words, it is possible that a peripheral variable will interact with the central variable to either enhance or reduce the processing of content. As stated in H1, a user is motivated to elaborate more if the content matches his/her preference more than otherwise. We further expect that such a difference in elaboration is larger in the presence of a sorting cue than not. This is because, if the content has a low level of preference matching, users will not find the content attractive and the presence of a sorting cue will not motivate or help them much in sorting through the different offers. On the other hand, if the web content matches users' preferences well, users will face a more complex choice that involves ranking a number of competing offers. The presence of a sorting cue becomes relevant and motivates users to scrutinize content to a larger extent. Users will have a larger number of thoughts, as reflected in a more polarized elaboration between high-level and low-level preference-matching content when a sorting cue is present than otherwise. Therefore, we hypothesize the following.

**Hypothesis 5 (H5).** The difference in the extent of elaboration between high-level and low-level preference-matching content will be larger for content with a sorting cue than for content without a sorting cue.

According to the ELM, a high level of elaboration only implies that the merits of the recommended item are fully explored and scrutinized. It does not necessarily lead to acceptance of the item. Even if the presence of a sorting cue leads to a heightened level of elaboration for preference-matching content, its effect will diminish at the choice stage when the decision is driven mainly by preference matching. Therefore, we hypothesize the following.

**Hypothesis 6 (H6).** A sorting cue has no effect on choice outcome.

### 3.2.2. Recommendation Set Size

A central question that needs to be addressed in developing a web personalization strategy is how many offerings should be recommended to the user (Murthi and Sarkar 2003). In practice, commercial websites vary in their strategy for determining the number of personalized recommendations. Some sites tend to offer a large number of recommendations. For instance, Amazon.com offers a large number of recommendations to new customers. On the other hand, Barnes&Noble.com provides two recommendations for each product category (e.g., nonfiction books, action/adventure DVDs) to a new user and also provides a hyperlink, “more recommendations,” for each category.

In this research, recommendation set size is defined as the number of personalized offers presented to the user. Will set size affect the attention level of users? Previous research suggests that the ability to attract attention depends on the saliency of the visual objects (Van der Heijden 1992, Vecera and Farah 1994). Portions of the visual field to which an individual’s attention is drawn are referred to as “visual saliency” to that individual (Taylor and Thompson 1982). After controlling for potential factors that may induce visual saliency (e.g., sharp color contrast, blinking objects), a user is more likely to be attracted by a larger object. This is because their scanning bandwidth, in terms of attentional resources, is limited, so they tend to start their information exploration from a location on a web page on which they can easily land. Because a large set will provide a larger “landing strip” for the user’s eyes, we propose the following hypothesis.4

**Hypothesis 7 (H7).** Content in a large recommendation set is more likely to attract attention than content in a small recommendation set.

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4 The hypothesized relationship is conditional on the assumption that all other sources of visual saliency are controlled for.
Unlike sorting cues, recommendation set size 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 rather obvious for a large set, as users simply are not able to evaluate all items because of their limited cognitive capacity (Lachman et al. 1979, Wyer and Srull 1989). However, when the number of items is small, users are more motivated to explore additional items as long as they are within their cognitive limits. Such behavior is driven either by variety seeking (McAlister and Pessemier 1982) or a desire to search for better alternatives. Thus, within their cognitive constraints, users are likely to exert effort proportional to the amount of content generated by the personalization agent. Beyond that, additional items will not be considered. We would like to argue that after factoring in variety seeking and the desire for better alternatives, there is no intrinsic processing heuristic related to recommendation set size even for a small set. It follows that to test the direct effect of recommendation set size on elaboration, we need to normalize set size for each test condition and to ensure that the number of offers under each condition is within the cognitive limit of an average person. We hypothesize the following:

**Hypothesis 8 (H8).** Recommendation set size has no effect on the level of elaboration after adjusting for the number of offers in the set.

While we argue that recommendation set size has a null effect, we expect that set size leads to biased processing by interacting with the level of preference matching in content elaboration. This effect, again, is conditional on the size of the recommendation set being within the limit of a person’s cognitive capacity. Biased information processing is said to take place when the amount of elaboration between high-level and low-level preference-matching content differs to a larger extent for a small set than for a large set. This is because a small set indicates a sense of selectivity and relevance when it is supplemented with good-quality content. On the other hand, if users find that the personalized offers are of low quality (i.e., they do not match their preferences), they will have less motivation to explore further. Thus, the effect of preference matching on elaboration becomes more polarized under the small set condition, as stated in the following hypothesis.

**Hypothesis 9 (H9).** The difference in the level of elaboration between high-level preference-matching content and low-level preference-matching content will be larger for content from a small recommendation set than for content from a large recommendation set.

In terms of choice outcome, recommendation set size should not increase/decrease the likelihood of selecting the recommended items. As long as a sufficient level of elaboration has occurred, the decision will be driven mainly by the outcome of the central route of elaboration. Thus, we hypothesize the following.

**Hypothesis 10 (H10).** Recommendation set size has no effect on choice outcome.

### 3.3. Personal Disposition—Need for Cognition

Previous studies indicate that personal disposition plays a key role in the evaluation of a persuasive message (Areni et al. 2000); that is, the same web content will create different levels of elaboration based on the personal characteristics of the receiver. One salient personality trait reported in the literature is need for cognition (NFC). Cohen et al. (1955) originally conceptualized NFC as “a need to structure relevant situations in meaningful, integrated ways. It is a need to understand and make reasonable the experiential world” (p. 291). Cacioppo and Petty (1982) modified this definition to reflect a more general “tendency to engage in and enjoy thinking” (p. 119). We anticipated that this trait would be useful for identifying individuals who are likely (versus unlikely) to generate elaborated inferences spontaneously.

Research has found that high-NFC individuals: (a) search for more information when making decisions (Verplanken 1993), (b) engage in more effortful processing of persuasive messages (Haugtvedt et al. 1992, Roehm and Sternthal 2001), (c) are more open-minded (Cacioppo and Petty 1982), (d) enjoy more effortful cognitive tasks (Larsen et al. 2004), (e) develop more complex causal explanations for the

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5 As in H8, we need to normalize the number of items under each set-size condition.
behavior of others (Fletcher et al. 1986), (f) hold attitudes that are more persistent over time and resistant to persuasion attempts (Haugtvedt et al. 1992), and (g) devote more topic-relevant thought to persuasive communications, than do low-NFC individuals (Cacioppo et al. 1983, Haugtvedt et al. 1992). Individuals with high NFC tend to make greater and longer lasting attitude changes, assuming the arguments in the message are strong (Cacioppo et al. 1983, Haugtvedt et al. 1992, Petty and Cacioppo 1981).

Because the attention stage does not normally involve a lot of cognitive effort, we will focus on the last two stages of information processing: elaboration and choice. Previous work on the ELM indicates that NFC serves as a moderator of elaboration via the central route (Haugtvedt et al. 1992). According to Petty and Cacioppo (1986a), the effect of NFC is called objective processing. It does not exert a direct effect, but affects the extent and direction of elaboration in an objective way. In other words, if NFC enhances the processing of personalized content, high-NFC users’ thoughts and attitudes should be more polarized between high-level and low-level preference-matching content than those of low-NFC users. Thus, we hypothesize the following.

Hypothesis 11 (H11). There is an interaction effect between NFC and the level of preference matching in the elaboration of personalized content, with preference matching having a more salient effect on high-NFC users than on low-NFC users.

In the ELM, acceptance of the position advocated in a message is largely driven by the merits of its arguments. As indicated in previous research (Areni et al. 2000), the effect of quality on the acceptance of a message is moderated by the user’s motivation to elaborate, as reflected in the user’s level of NFC. Thus, we hypothesize the following.

Hypothesis 12 (H12). There is an interaction effect between NFC and the level of preference matching on choice outcome, with preference matching having a more salient effect on high-NFC users than on low-NFC users.

We conducted a series of studies to test the above hypotheses. The research design is described in the next section.

4. Setup of the Field Experiment

4.1. Participants

Three studies were conducted based on an online field experiment involving the choice of ring-tone downloads for mobile phones. We cooperated with a major mobile data services content provider in Hong Kong to conduct the studies. The provider offers ring tones, games, and other content to mobile users. Emails were sent to 40,000 registered users of the content provider to recruit subjects for the studies. The subjects were randomly streamed into different cells in an array of experimental designs. We received 3,267 completed responses in total. Data from 1,001 distinct users were used to test the above hypotheses. The rest were assigned to cells that were beyond the scope of the current research.

All the subjects were ring-tone users. As a token of appreciation, the respondents were given a free ring tone for their mobile handsets and a chance to join a lucky draw for a special gift. To provide further incentive for the subjects to make accurate responses to our questions, those who successfully completed the experiment received a free individualized personality report. The study lasted for six weeks from mid-November 2003 to early January 2004.

4.2. Procedures

All the participants received an e-mail about the availability of a personalization service that was to be incorporated in the ring-tone download website. This service would have a customized layout, and users would have some ring tones recommended to them based on their ring-tone download history and singer preferences. The participants were invited to go to the website and fill in a questionnaire to evaluate the site’s performance.

The respondents to our online invitation were randomly assigned to the three studies. Each study was divided into three parts. First, the subjects were asked to fill in a questionnaire about their demographic information, ring-tone download habits, and personality. Second, we asked the subjects to indicate their preferences for rhythms and singers. Finally, all the participants entered a web page that had 12 ring-tone

choices. They were asked to select one ring tone from the list to download. All click streams were recorded.

A pretest with 56 subjects was conducted to validate the questionnaire and test the ring-tone download system performance. The subjects were able to complete the whole process in 25 minutes. These 56 subjects agreed that the navigation process and the selection task were smooth.

4.3. Elicitation of Ring-Tone Preference
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 singers. This log contained the actual ring-tone purchases of 7,858 distinct users. There were 66,795 transactions dated from August 2002 to November 2003. These users downloaded ring tones from 175 distinct singers. We chose the top 18 singers, who accounted for 32,869 (49.21%) out of 66,795 download transactions. These transactions were conducted by 6,474 (82.39%) distinct users.

We then formed a pool of 72 ring tones from 18 singers (four ring tones per singer). In general, there were two ring tones with fast rhythms and two with slow rhythms for each singer. The ring tones in the same rhythm category were assigned a recommendation priority based on the information obtained from the Hong Kong Music Billboard. All the subjects received a list of 12 ring tones, and they had to choose one from this list.

4.4. User Interface Design
All 12 ring tones were presented to a subject on a single page. The subject was not required to scroll down the page to view the ring tones. A typical page layout is shown in Figure 4. Six (or three) ring tones were presented on the right-hand side of the web page under Personalized Recommendations, whereas the other six (or nine) were presented on the left-hand side under Other Offers. There were no banner ads or other links on the web page. The title of the song associated with each ring tone was used as a label, and the singer of the song was also indicated.
All titles and singers were labeled in Chinese. For each ring tone, there were two buttons: one labeled “trial listening” and the other labeled “download.” When a subject pressed the “trial listening” button, an audio file of the selected ring tone was streamed to the subject’s client machine. The subject could listen to the ring tone using popular multimedia players, such as Microsoft Media Player or Real Player. There was no restriction on the number of times the subject could listen to the ring tone. A log of all the mouse clicks carried out by a subject was kept. When a subject pressed the “download” button, the selected ring tone was sent to the subject’s mobile phone.

5. Three Studies on Personalized Ring-Tone Downloads

In the following, three studies are presented, which were conducted based on the procedure mentioned in §4.2. Table 1 shows the independent variables for each study and the level of manipulation. Table 2 provides a list of dependent variables for each study, grouped according to the different stages of the information-processing model.

5.1. Study 1: Preference Matching and Sorting Cue

Study 1 examined the effect of preference matching and sorting cue on each stage of information processing. All the subjects received six ring tones under the column personalized offers and another six under the column other offers. There were two levels of manipulation of preference matching: personalized recommendation and randomized recommendation. Under the personalized recommendation condition, the list of recommended ring tones came from the subject’s favorite singers and preferred rhythms. Under the randomized recommendation condition, the list of ring tones was randomly extracted from the ring-tone pool.

There were two levels of manipulation of sorting cue: with a sorting cue and without a sorting cue. For the groups that received a sorting cue, colorful text and shadows were used to highlight one particular personalized recommendation to indicate that it was the best choice for the subject. This highlighted item was located at the top of the list (see Figure 4). For the groups that did not receive a cue, the six personalized recommendations were all presented on a vertical list. No single item was highlighted.

In terms of the operationalization of the dependent variables, attention was measured using a binary variable indicating whether the first item clicked by a subject was located at the top of the personalized offer column (i.e., the position of the cued item). Elaboration was measured by the number of trial listening at the top position of the personalized offer column. Finally, choice outcome was measured using a binary variable indicating whether the cued ring tone was selected as the final choice.

5.1.1. Results on Attention and Elaboration.

A two-way ANOVA was conducted, with sorting cue and preference matching as the explanatory variables. A manipulation check of preference matching was also conducted, the results of which were satisfactory.7 As shown in Table 3, the results indicated

7 We conducted a manipulation test by developing an instrument with the following items: (1) The ring-tone offers under the “personalized recommendations” column are my preferences; (2) The ring-tone offers under the “personalized recommendations” column are good; (3) The ring-tone offers under the “personalized recommendations” column are my favorites; and (4) I think the ring-tone offers under the “personalized recommendations” column are what I want. Responses to these questions were measured on a 7-point Likert scale with 1 = strongly disagree and 7 = strongly agree. All the subjects in the field experiment were included and were split into the personalized recommendation group and the randomized recommendation group. The reliability of the four-item construct was 0.62. The results of an ANOVA test indicated a significant difference (p < 0.05) between the two groups. The mean of the personalized recommendation group was 6.21, whereas the mean of the randomized recommendation group was 5.03.
that the presence of a sorting cue does attract attention: 37.50% of the subjects clicked on a cued item first, whereas only 15.19% clicked on the same item without sorting cue, supporting H3 ($\chi^2(1) = 26.09, p < 0.01$). Also, the ring tone associated with a sorting cue was elaborated more (mean = 2.08) than one without a cue (mean = 1.27). On average, the subjects listened to a cued ring tone twice ($F(1, 481) = 79.82, p < 0.01$), supporting H4. Moreover, the subjects were willing to expend more effort in considering the top ring tone under the personalized recommendation condition (mean = 1.98) than under the randomized recommendation condition (mean = 1.33), supporting H1 ($F(1, 481) = 51.59, p < 0.01$). Contrary to H5, there was no interaction effect between sorting cue and preference matching ($F(1, 481) = 0.11, p > 0.1$). Figure 5 depicts the effects of sorting cue and preference matching on information elaboration.

<table>
<thead>
<tr>
<th>Table 3</th>
<th>Results of Study 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample size</td>
<td>486 (222 females and 263 males; Average age = 23.67 years old)</td>
</tr>
<tr>
<td>Design</td>
<td>2 (preference matching) × 2 (use of a sorting cue) between-group design</td>
</tr>
<tr>
<td>Effects on attention</td>
<td>38% with a sorting cue, 15% without a sorting cue</td>
</tr>
<tr>
<td>Effects on elaboration on cued item</td>
<td>1.98 personalized, 1.33 randomized</td>
</tr>
<tr>
<td>Preference matching (H1***), Use of a sorting cue (H4**), Interaction effect (H5)</td>
<td>2.08 with a sorting cue, 1.27 without a sorting cue, 2.39 personalized, with a sorting cue, 1.66 randomized, with a sorting cue, 1.51 personalized, without a sorting cue, 1.02 randomized, without a sorting cue</td>
</tr>
<tr>
<td>Effects on choice</td>
<td>31% personalized, 20% randomized</td>
</tr>
<tr>
<td>Preference matching (H2**), Use of a sorting cue (H6***)</td>
<td>31% with a sorting cue, 21% without a sorting cue</td>
</tr>
</tbody>
</table>

* indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$. 

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5.1.2. Results on Choice Outcome. A logistic regression was conducted with the same explanatory variables as in the ANOVA analysis. The dependent variable was acceptance of a ring tone at the top of the personalized offers column. The results show that the ring tones under the personalized recommendation condition (31.37%) were downloaded more often than those under the randomized recommendation condition (20.43%), supporting H2 ($\chi^2(1) = 42.21, p < 0.01$). Contrary to H6, the use of a sorting cue did affect the final choice ($\chi^2(1) = 10.55, p < 0.01$).

5.2. Study 2: Preference Matching and Recommendation Set Size

Study 2 focused on the effect of preference matching and recommendation set size. In this study, the subjects received six (or three) ring tones under the column personalized offers and another six (or nine) under the column other offers. The manipulation of preference matching was the same as in Study 1. There were two levels of manipulation of recommendation set size: three recommendations (small set) and six recommendations (large set). These two levels were determined by making reference to the work of Narayana and Markin (1975), which reported that the mean evoked-awareness set size was between 3.5 and 10.6 brands. We therefore defined the lower bound to be three. Also, Simon (1979) reported that the number of information chunks that can be concurrently processed is seven. To allow for an equal number of items for both the personalized offers and other offers for the large-set condition, we defined the upper bound to be six. The total number of ring tones was fixed at 12. The small-set condition had three ring tones under personalized offers and nine under other offers, whereas the large-set condition had six ring tones under personalized offers and six under other offers. All the ring tones under other offers were randomly extracted from the remaining pool.

The operationalization of attention was different from that in Study 1. Here, we focus on the difference between two columns, personalized offers and other offers, instead of a single cued item as in Study 1. Attention was measured by a binary variable indicating whether the first item clicked on by a subject was in the personalized offers column. There were two measures of information elaboration: For the small-set condition, information elaboration was measured by the total number of trial listening in the personalized offers column. For the large-set condition, information elaboration was measured by the total number of trial listening in the personalized offers column divided by two to normalize the number of items. Choice outcome was measured by a binary variable indicating whether the selected ring tone was downloaded from the personalized offer column.

5.2.1. Results on Attention and Elaboration.

A two-way ANOVA was conducted, with recommendation set size and preference matching as the explanatory variables. Table 4 summarizes the results of the ANOVA test. When the subjects had a large set to choose from, 59.60% of them first clicked on the personalized offers, while only 28.57% of them first clicked on the personalized offers when they had a small set from which to choose. As hypothesized, set size had a main effect on attracting attention ($\chi^2(1) = 49.17, p < 0.01$), supporting H7. Consistent with H8, a large set did not lead to more elaborations. The subjects in the small set sampled 2.87 ring tones, and those in the large set sampled 2.79 (after normalization) ring tones ($F(1,512) = 0.63, p > 0.1$). The results show that the subjects were willing to expend effort in considering personalized recommendations (mean = 2.99), but not randomized recommendations (mean = 2.65). Again, H1 was supported ($F(1,512) = 13.63, p < 0.01$). This result is consistent with Study 1. Contrary to H9, we found no interaction effect between recommendation
5.3. Study 3: Preference Matching and Need for Cognition

We investigated the interaction effect between preference matching and need for cognition on information elaboration. Again, the manipulation of preference matching was the same as in Study 1 and Study 2. The NFC measurement was adapted from Cacioppo and Petty (1982). The subjects were asked to self-evaluate their NFC level on a seven-point scale anchored by “strongly disagree” and “strongly agree.” The five measurement items were: (1) I don’t like to have to do a lot of thinking [R]; (2) I try to avoid situations that require thinking in-depth about something [R]; (3) I prefer to do something that challenges my thinking abilities rather than something that requires little thought; (4) I prefer complex problems to simple problems; and (5) Thinking hard and for a long time about something gives me little satisfaction [R]. We used a median split (median = 0.95, range = −0.11 to 2.02) to classify the participants into a high-NFC group and a low-NFC group. The reliability of this construct was 0.87. Elaboration was measured by the number of trial listening of ring tones from the personalized list. The operationalization of choice outcome followed that of Study 2.

5.3.1. Results on Information Elaboration. Again, we conducted a two-way ANOVA with NFC and preference matching as the explanatory variables. The results are summarized in Table 5. The dependent variable was the number of personalized ring tones

<table>
<thead>
<tr>
<th>Table 4</th>
<th>Results of Study 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample size</td>
<td>516 (231 females and 285 males; Average age = 24.33 years old)</td>
</tr>
<tr>
<td>Design</td>
<td>2 (preference matching) × 2 (set size) between-group design</td>
</tr>
<tr>
<td>Effects on attention</td>
<td>60% large</td>
</tr>
<tr>
<td>Set size (H7++)</td>
<td>Effect on elaboration on personalized list</td>
</tr>
<tr>
<td>Preference matching (H1+++</td>
<td>2.99 personalized</td>
</tr>
<tr>
<td>Set size (H8)</td>
<td>2.87 small</td>
</tr>
<tr>
<td>Interaction effect (H9)</td>
<td>2.89 personalized, large (normalized)</td>
</tr>
<tr>
<td>5.78 personalized, large (not normalized)</td>
<td>2.66 randomized, large (normalized)</td>
</tr>
<tr>
<td>3.11 personalized, small</td>
<td>5.32 randomized, large (not normalized)</td>
</tr>
<tr>
<td>2.64 randomized, small</td>
<td>Effects on choice</td>
</tr>
<tr>
<td>Preference matching (H2+++)</td>
<td>52% personalized</td>
</tr>
<tr>
<td>Set size (H10++)</td>
<td>47% large</td>
</tr>
</tbody>
</table>

* indicates p < 0.1; ** indicates p < 0.05; *** indicates p < 0.01.

set size and preference matching on the depth of information elaboration (F(1, 512) = 1.51, p > 0.1). Figure 6 depicts information elaboration under different conditions.

5.2.2. Results on Choice Outcome. The results of a logistic regression showed that ring tones matching a participant’s personal preferences (51.77%) were downloaded more often than those from random offers (26.92%), supporting H2 (χ²(1) = 12.15, p < 0.01). This is consistent with Study 1. Also, we found that there was no significant main effect of recommendation set size on choice outcome, supporting H10 (χ²(1) = 2.96, p < 0.1).
Table 5  Results of Study 3

<table>
<thead>
<tr>
<th>Sample size</th>
<th>237 (99 females and 138 males; Average age = 23.02 years)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Design</td>
<td>2 (preference matching) × 2 (NFC) between-group design</td>
</tr>
</tbody>
</table>

Effects on elaboration on personalized list:

- Preference matching (H1***): 3.40 personalized, 2.48 randomized
- Need for cognition: 3.03 high NFC, 2.81 low NFC
- Interaction effect (H1***): 3.72 personalized, high NFC, 3.02 personalized, low NFC, 2.33 randomized, high NFC, 2.60 randomized, low NFC

Effects on choice:

- Preference matching (H2***): 66% personalized, 28% randomized
- Need for cognition: 48% high NFC, 45% low NFC
- Interaction effect (H2***): 74% personalized, high NFC, 56% personalized, low NFC, 22% randomized, high NFC, 35% randomized, low NFC

* indicates p < 0.1; ** indicates p < 0.05; *** indicates p < 0.01.

listened to. The results show that the subjects were willing to spend effort on considering real personalized offers (mean = 3.40), but not randomly generated offers (mean = 2.48). Again, H1 was supported ($F(1, 233) = 29.11$, $p < 0.01$). This is consistent with the results of the previous two studies. As hypothesized, there was an interaction effect between NFC and preference matching ($F(1, 233) = 8.39$, $p < 0.01$), supporting H11. Figure 7 depicts information elaboration under different conditions.

5.3.2. Results on Choice Outcome. Again, a logistic regression was conducted to test the effect on choice outcome. Similar to Study 2, the dependent variable was acceptance of a ring tone on the personalized list. The results show that ring tones matching subjects’ preferences (66.12%) were downloaded more often than were random offers (27.59%), supporting H2 ($\chi^2(1) = 38.81$, $p < 0.01$). Again, the result is consistent with the previous two studies. Also, there was an interaction effect between NFC and preference matching ($\chi^2(1) = 9.71$, $p < 0.01$). Subjects with low NFC tended to rely on personalized recommendations, whereas those with high NFC could distinguish real personalized offers from randomized offers. It was apparent that a high level of NFC will polarize the outcome between personalized recommendation and randomized recommendation conditions. Thus, H12 was supported.

6. Discussion

Table 6 summarizes the major findings of the three studies. First, there is strong evidence across all three studies that matching users’ preferences is key to heightening elaboration and influencing users’ choice of personalized offers. The findings fit well with the ELM framework that preference matching was a central variable in persuading users to accept the personalized offers.

Second, a large set did attract users’ attention. However, the results are not conclusive for elaboration and choice. The hypothesized interaction effect of set size and preference matching on consideration (H9) was not significant. While there is evidence that the null hypotheses related to elaboration and choice (H8 and H10) should not be rejected, our power analysis indicated a small power for both tests (Cohen 1988). Prior to conducting Study 2, we estimated that for a
Table 6  Summary of Findings

<table>
<thead>
<tr>
<th>Hypotheses</th>
<th>Study 1</th>
<th>Study 2</th>
<th>Study 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1: Content with a high level of preference matching leads to more</td>
<td>$p &lt; 0.01$</td>
<td>$p &lt; 0.01$</td>
<td>$p &lt; 0.01$</td>
</tr>
<tr>
<td>elaboration than does content with a low level of preference matching.</td>
<td></td>
<td></td>
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<tr>
<td>H2: The decision to accept a personalized offer is more likely with a</td>
<td>$p &lt; 0.01$</td>
<td>$p &lt; 0.01$</td>
<td>$p &lt; 0.01$</td>
</tr>
<tr>
<td>high level of preference matching than with a low level of preference</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>matching.</td>
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<td></td>
<td></td>
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<tr>
<td>H3: Content with a sorting cue is more likely to attract attention than</td>
<td></td>
<td>$p &lt; 0.01$</td>
<td></td>
</tr>
<tr>
<td>content without a sorting cue.</td>
<td></td>
<td></td>
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<tr>
<td>H4: Content with a sorting cue is more likely to induce elaboration than</td>
<td></td>
<td></td>
<td>$p &lt; 0.01$</td>
</tr>
<tr>
<td>content without a sorting cue.</td>
<td></td>
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<tr>
<td>H5: The difference in the extent of elaboration between high-level and</td>
<td></td>
<td></td>
<td>Not supported</td>
</tr>
<tr>
<td>low-level preference-matching content will be larger for content with a</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>sorting cue than for content without a sorting cue.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H6: A sorting cue has no effect on choice outcome.</td>
<td></td>
<td></td>
<td>Not supported</td>
</tr>
<tr>
<td>H7: Content in a large recommendation set is more likely to attract</td>
<td></td>
<td>$p &lt; 0.01$</td>
<td></td>
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<tr>
<td>attention than content in a small recommendation set.</td>
<td></td>
<td></td>
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<tr>
<td>H8: Recommendation set size has no effect on the level of elaboration</td>
<td></td>
<td>$p &gt; 0.1$</td>
<td></td>
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<tr>
<td>adjusting for the number of offers in the set.</td>
<td></td>
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<td></td>
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<tr>
<td>H9: The difference in the level of elaboration between high-level</td>
<td></td>
<td></td>
<td>Not supported</td>
</tr>
<tr>
<td>preference-matching content and low-level preference-matching content</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>will be larger for content from a small recommendation set than for</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>content from a large recommendation set.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H10: Recommendation set size has no effect on choice outcome.</td>
<td></td>
<td></td>
<td>$p &lt; 0.1$</td>
</tr>
<tr>
<td>H11: There is an interaction effect between NFC and the level of</td>
<td></td>
<td></td>
<td>$p &lt; 0.01$</td>
</tr>
<tr>
<td>preference matching in the elaboration of personalized content, with</td>
<td></td>
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<tr>
<td>preference matching having a more salient effect on high-NFC users than</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>on low-NFC users.</td>
<td></td>
<td></td>
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<tr>
<td>H12: There is an interaction effect between NFC and the level of</td>
<td></td>
<td></td>
<td>$p &lt; 0.01$</td>
</tr>
<tr>
<td>preference matching on choice outcome, with preference matching having</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>a more salient effect on high-NFC users than on low-NFC users.</td>
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</tbody>
</table>

sample size of around 500 and assuming a medium effect size, the powers of the statistical tests would be higher than the recommended value of 0.8. However, the post-hoc power analyses using the actual effect sizes obtained from Study 2 indicated a power of 0.1 and 0.31 for H8 and H10, respectively. The low powers were due to the much lower than expected effect sizes (0.04 for H8 and 0.15 for H10). A very much larger sample is needed to confirm the findings (e.g., over 4,000 for H8). Notwithstanding the actual small effect sizes, there is no evidence that the null hypotheses do not hold. This will be further discussed in the limitations section.

Third, contrary to our hypotheses, sorting cue was found to have no interaction with preference matching. Together with the significant main effect on elaboration, our findings suggest the role of sorting cue is more salient than that of a peripheral variable. This is further reinforced by its main effect on choice outcome. The surprising finding of a seemingly peripheral variable that turned out to be salient in all stages of information processing sheds new light on persuasion research. Traditional persuasion theories, including the ELM, have focused on attitude changes brought about by elaborating the merits of arguments embodied in a persuasive message. Their focus on message argument quality, although sufficient for contexts studied before, may fail to offer a complete account of the mechanism underlying persuasion tasks that involve choice outcome. The current findings indicate that peripheral persuasion variables may exert effects comparable to those of central variables.

Fourth, as hypothesized, NFC interacted with preference matching in affecting elaboration and choice outcome. While users with high NFC processed high-level preference-matching content to a larger extent than did low-NFC users, this discrepancy in elaboration became more salient with high-level
preference-matching content than otherwise. Similar findings were reported for choice outcome.

6.1. Limitations
There are a number of limitations to these studies that should be taken into account when interpreting the findings. First, our findings indicate that a large set attracts more attention, as it occupies a larger footprint on the screen. However, perceived visual saliency of a large set may be reduced as its footprint continues to grow. This is because the large set may become the “background” highlighting those items not in the set. As a consequence, the latter would be visually more salient than the large set. While we controlled for factors that might induce other kinds of visual saliency in our studies, one should interpret the findings with this limitation in mind.

Second, recommendation set size is sensitive to the cognitive bound of individual users. What seems to be large for some users may be small for others. Our operationalization of size with three as small and six as large may not accurately reflect users’ cognitive limitations. The difference may be too small to be detected, resulting in a very small effect size reported in the power analysis. Also, our attempt to normalize the set size by dividing the number of listening trials by two for the large-size condition is a straightforward measure, but it is only an approximation. It may not reflect the cognitive effort and fatigue that may scale in a nonlinear fashion as set size increases. The insignificant interaction effect between set size and preference matching could be attributed to the combined effect of our operationalization of set size and the normalization procedure.

Third, given the limited scope of the current research, we have focused primarily on variables that were expected to have a positive impact on elaboration and choice. However, there may be negative influences of peripheral cues such as bad design and improperly framed self-reference messages (e.g., misspelled names) that exert effects on user behavior. These negative influences were not studied in the current work.

Fourth, we focused on behavior related to personalized offers and did not hypothesize about behavior related to items listed under other offers. It is equally important, we believe, to understand how the proposed personalization variables affect the elaboration and choice of nonpersonalized offers as well as the overall elaboration of the website. Our decision to focus on personalized offers should not be taken as a reflection of the relative importance of the two sets of offers. It just reflects the limited scope of the current work.

Finally, we did not randomize the positioning of the personalized recommendations and the other offers. There may be asymmetry or lateralization attributable to the direction of reading and eye movements in the subject’s native written language. According to studies on human computer interaction (HCI), native English-language readers show left-right directionality, and Chinese readers read from left to right and from top to bottom (Nachshon 1985). Thus, Western readers exhibit more left-to-right saccades than do Middle Eastern readers, and East Asian readers exhibit more saccadic movement in the vertical direction (Scharine and McBeath 2002). Having said that, our research employed Chinese subjects—thus, placing the personalized list on the right-hand side actually reduced the bias toward the personalized offers.

6.2. Theoretical Contribution
This research contributes to the existing literature in several ways. First, the current work represents a pioneering effort to empirically study the effect of web personalization on user behavior. It augments previous research on personalization, which is predominantly analytical in nature (Murthi and Sarkar 2003). Second, by delineating the information processing of users into different stages, the current work is able to reveal the differentiating role of each variable and its effect on the attention, elaboration, and decision stages. It was found that sorting cue and recommendation set size were effective in attracting attention. Recent IS research also reports the saliency of web features (e.g., animation) in affecting users’ information-processing capabilities (Hong et al. 2004, Zhang 2000). In the current research, both sorting cue and recommendation set size were found to provide a way for a personalization agent to manipulate the saliency of the visual field.

Second, we made reference to the ELM to explain the effects of different variables by segmenting them through different routes. Our findings on elaboration indicate that web personalization influences users in
two major ways. On the one hand, it affects elaboration and decision making through the *central route* of persuasion by offering products that match the preferences of customers. The persuasiveness of the central route is supported in all three studies. On the other hand, a personalization agent can manipulate the presence (or absence) of a sorting cue and the number of recommended offers to invoke heuristic rules of users. This is the *peripheral route* of persuasion. Notwithstanding the limitations of our analysis on recommendation set size, we observed interesting results for the sorting cue. To our surprise, sorting cue exerted a significant influence in all stages of information processing. The saliency of its effect was comparable to that of preference matching. While this finding does not dispute the ELM as a relevant framework for studying web personalization, it does point out future research directions. Previous studies on the ELM were conducted in contexts that were very different from web personalization. Their primary focus was on attitude/opinion change rather than choice decision. Very often, the subjects in these studies were asked for their opinion (whether they agreed or disagreed) about a given statement. The central merits of the arguments accompanying the statement are the dominant factor affecting the persuasion outcome. On the other hand, the current research involves a choice process that could be cognitively taxing. The availability of decision aids such as a sorting cue could help to evaluate and rank competing offers. Our findings seem to suggest that the reduction of the cognitive load may become equally important as the quality of recommended items. While this should not be interpreted as contradicting the dichotomy between *central* and *peripheral* routes of persuasion, the current findings suggest a peripheral variable could play a pivotal role in the entire persuasion process.

Third, to probe further into the effect of sorting cue on elaboration and choice, we looked into the listening sequence of subjects under both personalized and randomized conditions, and studied how this sequence affects the choice outcome. As shown in Figure 8, a subject most likely downloaded the ring tone that he/she sampled first, indicating a priming effect on the sequence of elaboration for personalized ring tones. However, the priming effect became less salient with random offers. Studies on social cognition (Wyer and Srull 1989) indicate that the priming effect can be explained by activation of the targeted ring tone in the short-term memory. If the first ring tone matched the subject’s preference, the heightened level of activation would trigger a favorable affective response. The ring tone was then repeatedly activated and reinforced compared with other ring tones listened to in later parts of the sequence. This results in the sequence priming effect on choice outcome. On the other hand, if the first ring tone did not match the subject’s preference (i.e., randomized offers), the level of activation of the ring tone could not be reinforced as the subject sampled more ring tones, resulting in less affective arousal. Our observations are consistent with previous work on “decay of excitation” by Collins and Lofutus (1975), and work on impression formation based on the frequency and recency of the activating trait concept (Wyer and Srull 1989).

Finally, our findings reveal that personal disposition, as measured by *need for cognition* (NFC), played a pivotal role in influencing a user’s level of elaboration and choice outcome. Consistent with Petty and Cacioppo’s findings (1986b), we found that NFC is a moderator that induced objective processing of personalized offers. The lack of a direct effect on elaboration and choice reinforces the moderating role NFC plays in the process. Previous NFC-related ELM studies focused mainly on its effects on the level of elaboration and attitude change. Little work has been
conducted on NFC's effect in a choice setting. Our findings indicate that users who have little motivation to exert cognitive effort to evaluate the merits of alternatives tend to rely on recommendations suggested by the personalization agent. In addition to understanding the preferences and tastes of users to generate preference-matching content, it becomes equally important to understand users' personal dispositions. By doing so, a firm can maximize the leverage provided by a personalization agent. However, a major challenge for web service providers is to understand and derive the personality scores of their customers and prospects. Unless they are known, strategies that leverage on this finding cannot be realized. The challenge becomes identifying observable web behavior that correlates with NFC scores. To probe further into the topic, we have studied click patterns from the server log and correlated this information with the participants' NFC scores. We found that the correlations between NFC and the amount of repetitive listening to the same ring tone, and between NFC and browsing session time, were 0.23 and 0.25, respectively. These findings, although preliminary, provide evidence that observable web behavior may form the basis of a scoring index for personality traits.

6.3. Practical Implications

The web has become an essential channel for organizing a wide range of activities along the value chain of a firm, from procurement to distribution, and from promotion to customer support. According to the Personalization Consortium, the purposes of using IT to provide personalization are to (1) better serve the customers by adapting to their needs, (2) make the interaction efficient and satisfying on both sides, and (3) build a relationship to encourage repurchases. The current work views the task of web personalization as one of persuading a user by manipulating the content and layout of a message in web format. Practitioners would be interested in the implications of this research for the design of personalized websites. Some of these implications are summarized below.

Firms that contemplate using personalized web services for their current and prospective customers need to understand the availability and effectiveness of personalization tools. Online merchants need to know what the available personalization strategies are and which strategies best suit the firm's needs. Firms can invest heavily in acquiring personal data and developing sophisticated data-mining and tracking software with the aim of offering high-quality personalized content. This strategy is congruent with the central route of persuasion in the ELM. That is, by understanding and matching the preferences and needs of its customers, a firm is more likely to influence users in its promotion and sales efforts. The findings obtained from our studies support this. The quality of content matters.

In addition, the current work suggests that peripheral variables can also exert significant effects on web users. For example, sorting cue and recommendation set size were effective in attracting users' attention, and sorting cue was found to affect all stages of information processing. This finding is useful for firms structuring their web offerings and can make a personalization strategy more effective.

While the current work involves choice decisions, the findings are readily applicable to non-transaction-related corporate objectives such as promotion and brand building. For example, the likelihood that a message is implanted in the mind of online users increases with the level of elaboration. Our findings on communicating persuasive messages through online advertising can be leveraged by manipulating sorting cue and set size to capture viewers' attention and to heighten their elaboration of these messages. A high level of elaboration will generate associations with existing schema that can help to organize these messages in the user's memory and facilitate recall in the future.

According to The Economist (2004), self-service over the web will become a dominant mode of interaction between firms and customers in many industries. The replacement of human customer service agents with kiosks and the web will not only save costs, but will also, if done correctly, open a new channel of communication with customers. Its success depends on how well the personalization agent is able to understand the needs of individual customers and to package information tailored to their needs. As shown in our findings, preference matching is of central importance, yet other HCI features, in particular sorting cue, have salient effects on users. By carefully mapping out the relationship between these variables and
leveraging on their effects, firms can devise personalized self-services that can be delivered on a large scale cost-effectively.

6.4. Future Work
The current work can be improved in a number of ways. First, the variables investigated in the studies were restricted to preference matching, sorting cue, recommendation set size, and need for cognition. They are by no means exhaustive. Future work should explore more variables and different operationalizations of the current variables. For instance, in the current work, attention was operationalized as the user’s first click. It cannot capture precisely the concentration of attentional resources on different locations on a web page. The availability of an eye-tracking device would help to track the visual scanning field so as to capture more accurately the effect of HCI manipulations. Second, the product we used in our field experiment was ring tone; that is, a hedonic product. Its characteristics are very different from those of high-involvement products such as computers or repeat purchase items such as groceries. Third, the purpose of web personalization is to provide the right content in the right format to the right person at the right time. The timing issue is not addressed here. It would be very interesting to understand how timing affects the different stages of information processing. Should the users be exposed to personalized offers immediately after log-in or should the personalization agent present these offers during browsing or at the “checkout” stage? These are some of the ways in which the current work could be extended.

7. Conclusion
In summary, the current work has investigated the effects of web personalization in the context of persuasion. Using the ELM as the theoretical frame, web personalization was modeled to affect a user’s information processing through two sets of variables: (1) preference matching, and (2) sorting cue and recommendation set size. We also included a personality variable, need for cognition (NFC), which was expected to interact with preference matching. The use of the ELM as a theoretical frame enabled us to put the comparison of variables into perspective and to identify more clearly the role each variable plays in the processing of personalized content. This work represents a first step toward understanding how web personalization impacts web content elaboration and choice outcome. It also sheds light on the effectiveness of personalization to online merchants in offering unique experiences to their users. An improved understanding of how personalization affects the information processing of online consumers will be critical to firms to stimulate more web activities and to foster better relationships with their customers.

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