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RESEARCH ARTICLE

THE EFFECTS OF WEB PERSONALIZATION ON USER ATTITUDE AND BEHAVIOR: AN INTEGRATION OF THE ELABORATION LIKELIHOOD MODEL AND CONSUMER SEARCH THEORY[1]

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Web personalization can achieve two business goals: increased advertising revenue and increased sales revenue. The realization of the two goals is related to two kinds of user behavior: item sampling and item selection. Prior research does not provide a model of attitude formation toward a personalization agent nor of how attitudes relate to these two behaviors. This limits our understanding of how web personalization can be managed to increase advertising revenues and/or sales revenues. To fill this gap, the current research develops and tests a theoretical model of user attitudes and behaviors toward a personalization agent. The model is based on an integration of two theories: the elaboration likelihood model (ELM) and consumer search theory (CST). In the integrated model, a user's attitude toward a personalization agent is influenced by both the number of items he/she has sampled so far (from CST) and the degree to which he/she cognitively processes each one (from ELM). In turn, attitude is modeled to influence both behaviors—that is, item selection and any further item sampling. We conducted a lab study and a field study to test six hypotheses. This research extends the theory on web personalization by providing a more complete picture of how sampling and processing of personalized recommendations influence a user's attitude and behavior toward the personalization agent. For online merchants, this research highlights the trade-off between item sampling and item selection and provides practical guidance on how to steer users toward the attitudes and behaviors that will realize their business goals.

Keywords: Elaboration likelihood model, consumer search theory, web personalization, attitude persistence, attitude confidence

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Introduction

Web personalization is an automated process that identifies a user, collects his or her navigation patterns, analyzes known preferences of similar users, and estimates his or her specific preferences to tailor content for each user (Lavie et al. 2010). *Customization* and *personalization* both refer to the process of individualizing web content for each user; however, unlike customization, personalization is automated and does not require the user's explicit input or control to generate individualized content (Treiblmaier et al. 2004). Many applications have incorporated aspects of web personalization. For instance, websites may place content relevant to each user's individual needs on their topmost page for easy navigation (Kim and Chan 2003). Personalized search engines are capable of capturing users' browsing histories and producing individualized search results (Dou et al. 2009). Among the various applications, product recommendation is the most widely used application of web personalization. A personalization agent selects and advertises a small set of products in the form of recommendations that match a person's preferences, with the goal of influencing his or her decision making (Zanker et al. 2010). The focus of our research is on this latter aspect of web personalization—that is, personalized recommendations that are presented to online users by a personalization agent.

A personalization agent is often deployed to aid in attaining two major business goals: increased advertising revenue through user clicks on the website and increased sales revenue through purchasing. Realization of the two goals is related to two kinds of user behavior: item sampling and item selection. *Item sampling* takes the form of a user's clicks on personalized recommendations, whereas *item selection* involves the user choosing one of the personalized recommendations as the final choice (Tam and Ho 2005, 2006). In addition to their practical importance for creating revenue from personalization, these two behavioral outcomes correspond to informational usage and transactional usage, two categories proposed by Jansen et al. (2008) to characterize usage in e-commerce settings. The purpose of our research is to develop a theoretical model of these two behaviors and their attitudinal antecedents.

Prior literature does not provide a model of attitude formation and behaviors toward a personalization agent as a whole—that is, a personalization agent itself rather than the individual recommendations it produces. For example, Tam and Ho (2006) measured how much a user likes a particular recommendation but did not consider attitudes toward a personalization agent as a whole. We adopt an agent-level perspective, both because of the gap in the existing literature on personalization and because it allows us to address many of the practical questions that are of interest to merchants. For a merchant who introduces personalized recommendations to increase user clicks and advertising revenue, the potential benefit of personalization depends on the total number of recommendations a user clicks, rather than on any one recommendation. For a merchant who introduces personalized recommendations to convert each recommendation into a sale, the potential benefit of personalization depends on the likelihood that the user will finally select one of the recommendations to purchase. Both of these behavioral outcomes are modeled to depend on a user's attitude toward the personalization agent as a whole.

The elaboration likelihood model (ELM) is an appropriate basis for modeling the factors that influence attitude formation toward a personalization agent as a whole. The ELM models the effects of a user's elaboration of individual persuasive items on his or her overall attitude. Applied to the current setting, ELM models how a user's elaboration of individual recommendations influences his or her attitude toward the personalization agent as a whole, which in turn influences his or her decision to select a personalized recommendation as the final choice (Petty and Cacioppo 1986a, 1986b; Tam and Ho 2005). In the ELM, *elaboration* is defined as the extent to which a person carefully thinks about an argument (Petty and Cacioppo 1986a); that is, a personalized recommendation in our research context. We refer to this as *depth of processing*. Depth of processing of a personalized recommendation affects the user's attitude toward the personalization agent and, in turn, this attitude affects item selection.

Although the ELM models the effect of depth of processing on attitude and item selection, it does not model how many arguments a person comes to inspect in a given environment. In the web personalization context, the ELM illuminates the degree to which a user will cognitively process a given recommendation but not the number of recommendations that the user investigates, which is of interest to merchants who want to maximize user clicks. We appeal to consumer search theory (CST) to account for this. CST models the number of items that a person inspects in the completion of a search task (Stigler 1961). We refer to the number of items that a user chooses to inspect as *breadth of sampling*. In our integrated model, the ELM's depth of processing and CST's breadth of sampling combine to influence attitude formation, which in turn affects item selection. In addition, CST's breadth of sampling is a behavioral outcome in its own right, representing item sampling. The current research integrates the ELM with CST in a model that relates attitude formation toward a personalization agent as a whole, with both item sampling and item selection.

CST is a normative theory, while the ELM is a psychological theory. Our approach to synthesizing the two is to adopt a psychological framework while including variables that capture the intuitions of CST. From a theoretical perspective, using ideas from the ELM and CST, we include depth of processing and breadth of sampling in a research model that provides a rich conceptualization of the attitude formation process and the attitude–behavior link. The model distinguishes three aspects of attitude: valence, persistence, and confidence. Through distinguishing different aspects of attitude and different kinds of user behavior, we construct a richer conceptualization of the attitude–behavior link. From a practical perspective, the model shows how system parameters can be set to steer users toward different shopping behaviors, depending on what the merchant wishes to achieve from web personalization. At a more fundamental level, this research highlights the managerial imperative of prioritizing the business goals from web personalization because different behavioral outcomes sometimes conflict. In one example, attitude confidence results in decreased item sampling but increased selection of personalized recommendations. This research allows online merchants who are considering an investment in web personalization to evaluate and realize its potential benefits as well as possible drawbacks more thoroughly. Table 1 summarizes the ELM and CST.

The rest of this article is structured as follows. The next section introduces the theoretical underpinnings of this research, as building on ELM and CST. The subsequent section presents the hypotheses derived from our integrated ELM-CST model. We then describe the two studies and present the findings before discussing the research implications. The final section concludes the paper.

Theoretical Framework

Elaboration Likelihood Model (ELM)

The ELM is a persuasion theory (Petty and Cacioppo 1986a). When a person is exposed to a message, it models how the characteristics of the message influence the person's attitude formation and, subsequently, his or her behavior. Thus, the ELM forms a basis for modeling the influence of individual personalized recommendations on a person's attitude and his or her item selection. Specifically, the ELM identifies two qualitatively different routes to persuasion—central and peripheral—through which the message may influence attitudes. These two routes are characterized by depth of processing. When depth of processing is high, the ELM describes it as *the central route* to attitude formation, in which the person carefully processes the logic of the arguments presented in the message and scrutinizes the issue-relevant arguments. In contrast, when depth of processing is low, the ELM describes it as *the peripheral route* to attitude formation, in which the person processes the message based on associations and rules of thumb, without requiring a personal evaluation of the issue-relevant arguments presented. In this case, relatively simple cues in the message may influence his or her attitude. The person's depth of processing increases with his or her motivation and ability. The person's attitude toward the target (in our case, the personalization agent) influences his or her subsequent actions toward it. Figures 1 and 2 depict the basic ELM by Petty and Cacioppo (1986a). Figure 1 presents the influence processes from argument quality and peripheral cues. As this research focuses on the quality of web personalization (a kind of argument quality), Figure 2 presents a simplified model depicting the influence processes from argument quality only.[2]

Bhattacherjee and Sanford (2006) combined the basic ELM with the technology acceptance model (TAM) to take into consideration user perception of a technology in attitude formation. Specifically, in their reframing of the ELM, depth of processing moderates the effect of argument quality on perceived usefulness, rather than (directly) on attitude valence. Their extension is consistent with the logic of the ELM and neatly extends ELM to information systems attitude formation. In the current research, we adopt their insertion of perceived usefulness as an intervening variable that affects attitude valence, which leads to the structure shown in Figure 3.

IS researchers have used the basic ELM (Figures 1 and 2) or the ELM with TAM (Figure 3) to examine the communication between users and technology artifacts (Angst and Agarwal 2009; Bhattacherjee and Sanford 2006). However, prior IS research using the ELM included only the most basic characteristic of attitude—valence—that is, the direction and extremity of an attitude. This was the appropriate focus in the research settings of prior work (e.g., Tam and Ho 2005) in which participants navigated a personalized website and expressed (the valence of) their attitudes immediately afterward. However, attitudes may fade over time (Sengupta et al. 1997). To examine this, our study includes *attitude persistence*, a nonevaluative characteristic of attitude in the ELM that has not been addressed in previous personalization research. Attitude persistence refers to the extent to which an

[2]The two routes of processing are two endpoints in a continuum. By measuring depth of processing, this research examines if a person is doing more of central-route processing or peripheral-route processing. This research does not model or manipulate the effects of peripheral cues. Instead, we control the effects of peripheral cues in the lab and the field experiments.

Table 1. Elaboration and Sampling Perspectives

Theory	Elaboration Likelihood Model	Consumer Search Theory
Root disciplines	Cognitive psychology	Economics and mathematics
Nature of solutions	Descriptive	Normative
Purposes	To examine the factors that influence how people form their attitudes through elaborating a given piece of information	To model the point at which continued item sampling is no longer worthwhile, as a mathematical function
Core construct related to our integrated model	Depth of processing	Breadth of sampling
Role in the integrated model	To look at how a person elaborates a personalized recommendation to form his or her attitude toward the personalization agent, which in turn influence his or her item selection	To look at how many personalized recommendations a person samples to complete a shopping task

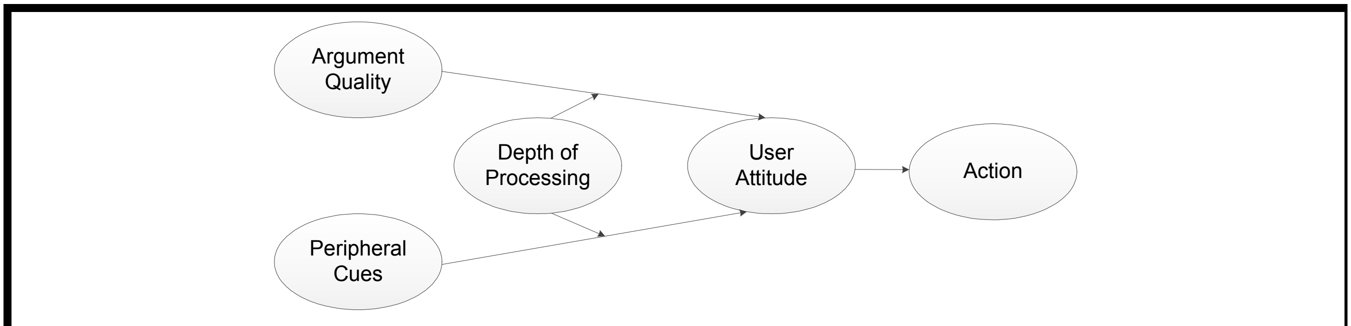


Figure 1. The Basic Elaboration Likelihood Model (ELM)

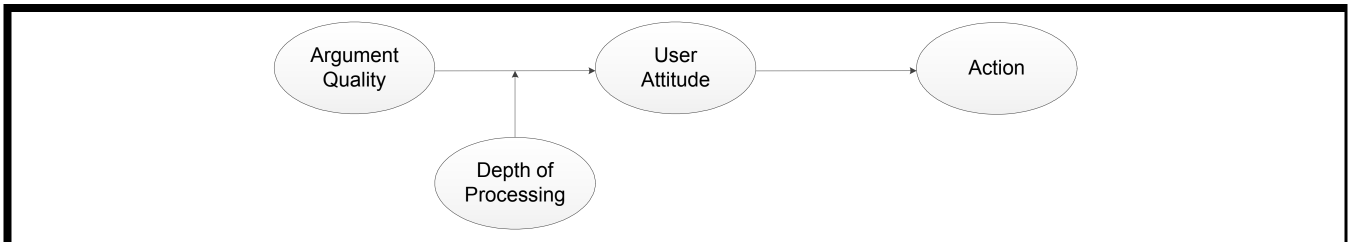


Figure 2. A Simplified ELM to Form the Basis of this Research

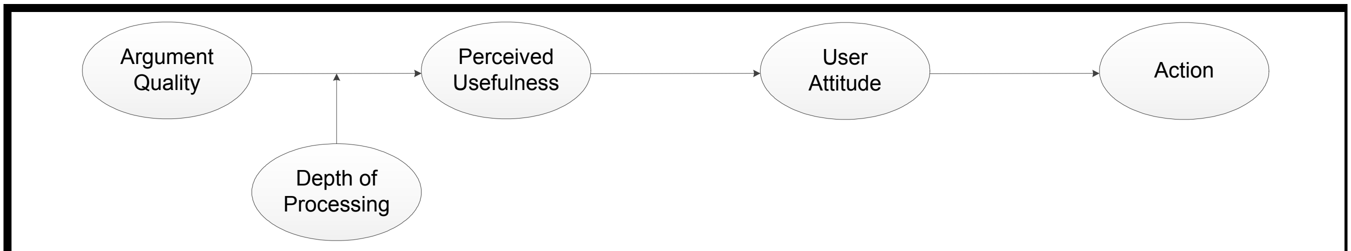


Figure 3. The Extended Elaboration Likelihood Model (Adapted from Figure 1 in "Influence Processes for Information Technology," A. Bhattacherjee and C. Sanford, *MIS Quarterly* (30:4), 2006, p. 809.)

attitude endures over time (Petty and Krosnick 1995). When a person holds a persistent attitude, this means that the person can easily access from memory the valence of a previously formed attitude. Introducing attitude persistence to the web personalization literature can bring out the longitudinal aspects of user attitude and behavior.

The main limitation of the ELM for understanding the effects of web personalization on user behavior is that, while it illuminates the effects of how information is processed, it does not consider how the user initially came to encounter the information. The ELM conceives of a person who is (passively) exposed to information but no account is made for how he or she came to be exposed to the information. This might be expected in a traditional *push* environment of broadcast communications, or enterprise systems in which detailed click flow is predetermined for standard transactions. In contrast, in e-commerce systems, a user often has control over the amount of the information he or she encounters. The user *pulls* the information. In our case of a personalization agent providing recommendations, the user controls how many of the agent's recommendations to sample. This issue is not addressed by Bhattacherjee and Sanford's model or ELM theory itself. Tam and Ho (2005) partially addressed this issue by studying the amount of personalized item sampling; however, they did not delineate the two dimensions—how much information a person explores and how deeply he or she thinks about it. The conceptual differences between the two dimensions become salient when attitude characteristics beyond valence are examined. This research extends the ELM to model what information the user encounters in addition to the ELM's original focus on the effects of how it is processed. As previously mentioned, we refer to these as breadth of sampling and depth of processing, respectively. To supplement ELM in this way, we draw on CST.

Consumer Search Theory (CST)

CST develops normative models of the process of searching for a good item (Grosfeld-Nir et al. 2009; Hey 1981; Seale and Rapoport 1997; Stigler 1961; Zwick et al. 2003). CST views the item source as a distribution and each act of inspecting an item is viewed as sampling an item from the distribution. Applied to our setting, the item source is a personalization agent and sampling its items is viewed as sampling items from a distribution. A central component of CST models is the *stopping rule*, which defines in mathematical terms the point at which the expected marginal benefit from sampling additional items is less than the marginal cost, at which time the person should stop searching and choose the best one from those sampled so far (assuming it is still available). Therefore, a model's stopping rule determines the number of items a person will have sampled before stopping. As mentioned earlier, the number of sampled items is referred to as breadth of sampling. By analyzing the factors that enter into the stopping rule formula, we are able to predict how situational variables affect the breadth of sampling that a user will conduct before stopping. One exogenous factor that enters into the stopping rule is the variance of the items, as will be explained in detail in the next section.

Another factor is the user's confidence in his or her evaluation of the item source (DeGroot 1968), which is his or her estimate of the mean value of items produced by the source. CST models that in the process of searching, apart from getting a satisfactory item, a user evaluates the item source based on the individual items from the source he or she has seen. In our context, the user evaluates the personalization agent as a whole based on the individual recommendations he or she has sampled. Further, CST models that a user recognizes that his or her evaluation of the item source as a whole might not be completely accurate, as the particular items that he or she sampled might not be representative of the item source's true capability. The stopping rule depends on the user's level of confidence in his or her evaluation of the item source, as will be explained in detail later. The user's confidence increases through increased sampling, resulting in a two-way temporal relationship between sampling and confidence: sampling increases confidence and confidence leads to reduced *subsequent* sampling.

As described, the concept of *confidence* appears in a mathematical form in CST, but it does not appear in the ELM; thus, it must be conceptualized in a way that fits into an ELM framework. In the mathematical terms of CST, the user's uncertain evaluation of the item source has variance, or a confidence interval (the CST literature uses the term *precision*). The consumer behavior literature includes an attitude confidence construct and, although it is conceived as a psychological construct, its definition and connection with other constructs mirror those from CST. In the consumer behavior literature, attitude confidence is operationalized by asking how certain the person is (Berger and Mitchell 1989), which can be seen as a psychological corollary to a confidence interval around a mathematical assessment. The consumer behavior literature also finds that attitude confidence depends on the number of times a person has seen a message (Haugtvedt et al. 1994); this is reminiscent of the effect of item sampling on confidence as it is modeled in CST. The difference is that, whereas the concern in the consumer behavior literature is with whether repetition of a single argument causes a person to remember it, the concern in CST is with how seeing a variety of different individual arguments gives the person more confidence in his or her evaluation of the item source as a whole. Based on all of this, we introduce into our extended ELM framework an attitude confidence construct that is based on CST theory. We define it as how certain a user is in his or her attitude and we conceptualize it as depending on the cumulative number of personalized recommendations that a user has sampled.

CST, a theory of consumer search, dovetails well with the ELM, a theory of persuasion and attitude formation. In both theories, a user evaluates an item source based on individual items that he or she has seen. CST adds a detailed model of how many items a user will ask to see and a feedback mechanism through which confidence in the evaluation affects subsequent sampling. Conversely, in spite of CST's strength in relating shopping to evaluation, CST's conceptualization of how a person evaluates a system takes the simplistic form of a perfectly executed mathematical estimate of a distribution's mean. The ELM complements this with a rich and empirically established model of attitude formation. Our general approach is to incorporate the ideas of CST into the attitude formation framework of Figure 3, our extended ELM adapted from Bhattacherjee and Sanford. In combination, the two theories form a more complete picture of how depth of processing and breadth of sampling influence a user's attitude toward a personalization agent and, in turn, how this attitude affects item selection and subsequent item sampling behavior. This is the conceptual basis of our model.

Two central variables that emerge from this framework are depth of processing, from the ELM, and breadth of sampling, from CST. Our model builds on this by tracing how these two elements affect characteristics of attitude beyond valence. Depth of processing is cognitive processing that takes place in a human brain. It influences how deeply the information is implanted in memory. In contrast, breadth of sampling captures a person's direct, behavioral experience with the personalization agent. It relates to the amount of evidence provided to the person to form an attitude. Depth and breadth are likely to influence different characteristics of an attitude. In the next section, we develop specific hypotheses that relate depth of processing to attitude persistence, and breadth of sampling to attitude confidence.

Hypothesis Development

Figure 4 presents our research model. In this section, we develop hypotheses to relate quality and variation of personalized items to a person's sampling of recommendations and selection of a recommendation from the personalization agent.

Depth of Processing and Attitude Persistence from the Elaboration Likelihood Model

We first look at the effect of depth of processing on attitude persistence. The ELM postulates that attitude persistence is associated with depth of processing performed on the part of the person in forming the attitude (Haugtvedt and Petty 1989; Petty and Cacioppo 1986a). When depth of processing is high, as it is when the message is processed via the central route, the person generates a series of thoughtful issue-relevant arguments for scrutiny. For thoughtful examination, the argument schema is compared multiple times with issue-relevant schema previously stored in the memory (Petty and Cacioppo 1986a, 1986b; Petty and Krosnick 1995; Sengupta et al. 1997). More processing leads to more access to memory schemas, resulting in stronger interconnections between the issue-relevant schemas previously stored in memory and the new argument schema (Priester and Petty 2003). Consequently, the attitude formed by deeper processing is more persistent.

In contrast, when depth of processing is low, as it is when the message is processed via the peripheral route, the person relies on simple cues. The cues provide some effective associations or allow some relatively simple inferences for the acceptability of the advocacy (Sengupta et al. 1997). One-time accessing of the issue-relevant schema may be ample to incorporate the affect or inference elicited by the peripheral cue. Thus, the formation of an attitude by the peripheral route involves considerably less cognitive work than that by the central route (Petty and Cacioppo 1986a). Additionally, it is possible that the peripheral schema invokes a "wrong" schema in memory that is irrelevant to the issue of evaluating the peripheral cue (e.g., is the color of the website good?) (Petty and Krosnick 1995). Consequently, the attitude formed by shallower processing is less persistent. Therefore, we anticipate that if a user carefully elaborates personalized items, it is likely that he or she will form a more persistent attitude toward the personalization agent:

H1: Depth of processing has a positive effect on the persistence of attitude that users form toward the personalization agent.

Breadth of Sampling and Attitude Confidence from Consumer Search Theory

We turn to CST for theory regarding breadth of sampling. Each CST model begins with a set of assumptions from which a stopping rule is analytically derived. Four main modeling assumptions that distinguish the various models are the objec-

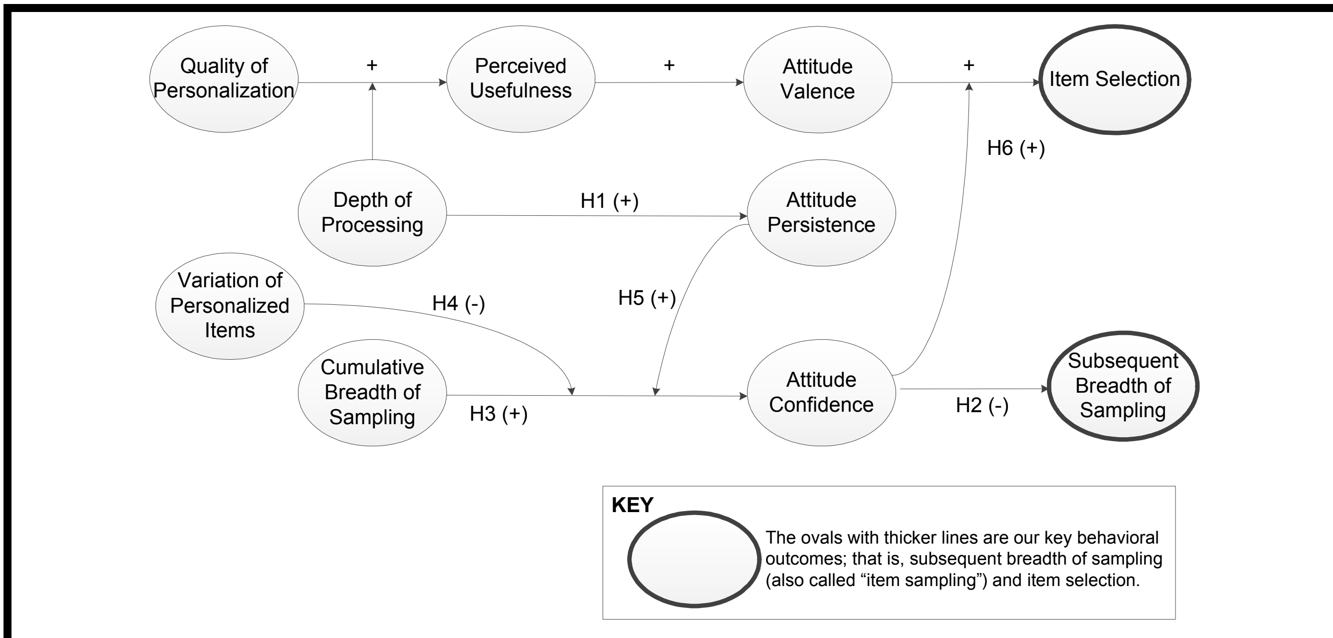


Figure 4. Research Model

tive function, the possibility of recall, the presence of search costs, and the level of information (Bearden et al. 2006; Freeman 1983; Hey 1981; Rapoport and Tversky 1970). For each, we briefly explain the modeling assumption that is most appropriate to our setting of e-commerce consumer shopping. Regarding the objective function, we adopt a model in which the person's objective is to maximize the (subjective) value of the selected item, net of the search cost (Stewart 1981). Other possibilities less applicable to our setting are "nothing but the best" (Gilbert and Mosteller 2006) or functions that depend only on the rank position of the selected item (Seale and Rapoport 1997). Regarding recall, we adopt a model *with* recall, which means that the person can go back and choose any item he or she saw during the course of the search. Other possibilities that are less applicable to our setting are that an item is definitely (Lippman and McCall 1976; Rothschild 1974) or possibly (Zwick et al. 2003) gone forever if not selected when first encountered. Models that allow recall necessarily include search cost as an additional modeling element (Grosfeld-Nir et al. 2009; Moorthy et al. 1997; Srivastava and Lurie 2001; Su 2008); otherwise, if recall were allowed and there were no search costs, the trivial optimal stopping rule would be to conduct an exhaustive search before deciding. Finally, we adopt models with partial information (DeGroot 1968), in which the person must learn about what is available during the course of shopping. The alternative that is less applicable to our setting is a full-information model (Rapoport and Tversky 1970), in which the person knows the mean and variance of the value of the available items, but such a model is considered to be unrealistic (Bearden et al. 2006) or even "absurd" (Rothschild 1974, p. 692) in the consumer context.

We adopt DeGroot's (1968) model, which is a Bayesian approach that meets all of the outlined criteria, is most appropriate to the web personalization setting, and has served as the basis for subsequent research (Albright 1977; Loch et al. 2001; Rothschild 1974). In this model, the stopping rule depends partly on the person's evaluation of the item source, so that, as part of the shopping process, he or she attempts to evaluate the item source as a whole, based on the individual items he or she encounters. Specifically, the personalized items have *subjective* value to a given person. The item values have mean, θ, and precision (inverse of variance), r. The person is constantly trying to estimate θ, which represents the average (subjective) value of the personalized items that the agent recommends. The estimate of θ takes the form of a distribution, reflecting that the person has uncertainty about his or her estimate, since he or she has sampled only a few of the recommendations. In particular, assume that a person begins with a prior estimate that we denote as $\hat{\theta} \sim N(\mu, \tau)$. This means that his or her estimate of θ, which is denoted $\hat{\theta}$, is centered on μ and has precision τ.[3] As the person samples an additional item that turns out to have the (subjective) value

[3]Notably, θ is the actual mean of personalized items and μ is the mean of a person's estimate of θ, r is the precision (inverse of variance) of personalized items, and τ is the precision of a person's estimate of θ.

of x, he or she updates his or her estimate of θ so that the posterior is $\hat{\theta} \sim N([\tau\mu + x)/(\tau + r)], \tau + r)$. Note that the estimated mean, μ, is higher if x is higher. In addition, if the precision of the estimate is τ before sampling an item, it is $\tau + r$ afterward. The general form of the stopping rule under this approach, which will form the basis for our theoretical perspective and predictions, is as shown in Equation 1.

Bayesian stopping rule: The person should continue sampling until he or she is holding an item whose value v satisfies

$$v > \mu + f\left(\frac{\tau}{\tau + r}, c\right) \tag{1}$$

in which v is the value of the highest-valued item found so far; μ is the person's most up-to-date estimate of the mean (subjective) value of the available personalized items; τ is the precision of the user's estimate; r is the inverse of variance of the items (i.e., precision of the items); c is the constant cost of sampling one more item; and $f(\,)$ is a function that is decreasing in c and in $\frac{\tau}{\tau + r}$, implying that it is decreasing in τ and increasing in r. The ratio $\frac{\tau}{\tau + r}$ represents the current precision of the estimate (τ) relative to what the precision would be if one more item were sampled ($\tau + r$). The intuition is that the stopping rule is nearing invocation to the extent that the user already knows of an item that is better than the item source's mean, the precision of his or her estimate of the item source's mean is already fairly high relative to the increase that would result from more sampling, and search costs are high.

The first hypothesis that follows from this equation is that, as the user gains confidence in his or her attitude toward the personalization agent, he or she is closer to invoking the stopping rule. In Equation 1, this is represented by the fact that $f(\,)$ is decreasing in $\frac{\tau}{\tau + r}$, which implies that it is decreasing in τ. The intuition behind this part of the equation is that as long as a user lacks confidence in his or her attitude toward the personalization agent, he or she has reason to continue sampling from it, hoping that the personalization agent's true capability may actually be better than the items he or she has seen so far. As the user gains confidence that the items he or she has seen are representative, this hope fades, bringing him or her closer to invocation of the stopping rule. As described earlier, our model uses the psychological construct of confidence in one's attitude in place of the mathematical notion of the precision of a distribution. We predict:

H2: Confidence in one's attitude toward the personalization agent has a negative effect on subsequent breadth of sampling from the personalization agent.

Additional hypotheses regard the determinants of confidence. According to Equation 1, with each act of sampling, the precision τ increases. Reframed in psychological terms, the user's confidence in his or her estimate of the mean of personalized recommendations increases with each additional item sampled. The model makes a more specific prediction: that with each additional item sampled, precision in the overall estimate increases by r, which is the inverse of variance of the personalized recommendations. This means that the increase in the user's confidence that occurs with each item that is sampled is greater when the distribution of personalized recommendations is less varied. As an example, whether the user sees three personalized items of similar (subjective) quality to which he or she assigns three similar values (e.g., the perceived values of the three items are 4, 5, and 6) or three personalized items of different quality to which he or she assigns diverse values (e.g., 0, 5, and 10), he or she will estimate that the personalization agent produces items with mean 5; however, he or she will feel more confident in this estimate in the former case. Based on the model, we hypothesize:

H3: Cumulative breadth of sampling from the personalization agent positively influences confidence in one's attitude toward the personalization agent.

H4: Item variance negatively moderates the positive effect of cumulative sampling breadth on attitude confidence.

Effects among Nonevaluative Characteristics of Attitude from Both the Elaboration Likelihood Model and Consumer Search Theory

We augment CST's rational notion that confidence increases with the amount of sampling, with a psychological moderator based on the ELM. The ELM uses attitude persistence to capture a person's abilities to retrieve his or her previously formed attitude (Petty and Cacioppo 1986a, 1986b; Petty and Krosnick 1995). For a person holding a persistent attitude, any additional sampling of personalized items adds to the cumulative total of evidence in support of the attitude. In contrast, for a person holding a transient attitude, the cumulative effect of personalized sampling is weak, as the newly sampled items are used to form an attitude from scratch rather than to strengthen a retained attitude. Therefore, we theorize:

H5: Attitude persistence moderates the effect of cumulative breadth of sampling from the personalization agent on attitude confidence.

Effect of Attitude Confidence on Item Selection Behavior (Elaboration Likelihood Model Plus Consumer Search Theory)

Prior research on web personalization has assumed that a predictive relationship exists between a person's attitude (valence) toward the personalization agent and his or her actual behavior (Komiak and Benbasat 2006). In most personalization studies, a person's attitude (valence) has been operationally defined as his or her response to a set of verbal questions. Such measures provide a composite score that represents the person's favorableness toward the personalization agent. However, the underlying attitudes of two people with identical scores may differ in many other aspects that may affect the attitude–behavior link. Research using the ELM has provided empirical evidence showing that depth of processing moderates this link, such that users who arrive at a given attitudinal valence through deeper processing will be more likely to act on their attitude (Petty and Cacioppo 1986a). Other research has empirically found a related result: that attitude confidence moderates the relationship between attitude valence and user behavior (Fazio and Zanna 1978). Thus, the literature supports two ideas: depth of processing and/or attitude confidence moderate(s) the link between attitude valence and behavior. Since according to H1 and H5 depth of processing is modeled to affect attitude confidence, we hypothesize that (only) attitude confidence serves as the attitude–behavior link, with the effect of processing depth being subsumed. Specifically, we hypothesize that a person holding a more confident attitude is more likely to act according to his or her attitude valence than a person holding a less confident attitude. We anticipate:

H6: Attitude confidence moderates the relationship between attitude valence toward a personalization agent and actual selection from the agent.

Lab Study (Study 1)

We developed a personalized online bookstore using the online bookseller Amazon's web services programming interfaces. During a two-week period, participants visited our personalized bookstore multiple times to select books for their study and report their thoughts on sampled books. We chose books as our study context because they are experience goods in which user clicks are particularly meaningful in terms of inspecting an item and evaluating a personalization agent (Hauser and Wernerfelt 1990; Klein 1998). The lab study adopted a thought-listing technique to capture participants' depth of processing for testing H1. As such, participants were instructed to list the thoughts elicited by the sampled book on the website. This thought-listing technique has been widely adopted in other ELM studies (e.g., Cacioppo and Petty 1981; Petty and Cacioppo 1986a, 1986b; Petty et al. 1993), but it is nevertheless an obtrusive measure. The field study (reported in the next section) was designed to complement the lab study by increasing external validity. In the field study, to preserve the naturalness of the setting, participants were not asked to list their thoughts. The field study reaffirms the model, except for H1, which could not be tested in the field study.

Setup and Procedures

At the beginning of the lab study, participants completed a short questionnaire designed to collect demographic information. Subsequently, they were provided with a short task scenario describing an imaginary situation requiring them to select a book. The order of task scenario presentation was randomized to minimize bias. Appendix A presents all task scenarios.

Figures 5a and b show the interfaces of our personalized website. During the book selection process, participants could sample any number of books from the stock list and/or from the personalized list. After sampling, they wrote text comments to describe their thoughts relating to the sampled book. Throughout the process, the participants could add any number of books into their shopping basket then they chose one to be their item selection. Twenty-four hours after the previous item selection, they could log onto the website again and select another book.

There were pre-task and post-task questionnaires. In all pre-task questionnaires (except for that used in Session 1, which, as mentioned, concerned demographics), the participants reported their attitude toward the personalization agent in the online bookstore. After the selection task, they reported their attitude in the post-task questionnaires. To complete the study, participants repeated the book selection process four times.

Our database had 40,000 books from the Amazon book list. They were randomly divided into four pools of 10,000 books, one pool for one log-on session. When logging on, the same participant would see six new personalized recommendations on each visit. These recommendations appeared at the bottom

(a) Home Page of Bookstore Website | **(b) Web Page for Book Sampling**

Figure 5. Interfaces for the Personalized Bookstore Website

of every page. Good recommendations were supplied to half of the participants and poor recommendations were supplied to the other participants, to avoid any ceiling or floor effects of the variable quality of personalization. To generate good recommendations, our personalization system ranked books in each category according to Amazon popularity indices and customer feedback. The good recommendations came from the top 25 percent of popular books in the category relevant to a participant's study major. To generate poor recommendations, our personalization system randomly drew six items from the pool. All recommendations were labeled "Personalized Recommendations" on the study website.

Prior to the main study, we conducted a pilot test with 12 participants to check the download system performance. All participants could complete the entire process of one selection session within 20 minutes and confirmed that the book selection process was smooth.

User Interface Design

The home page of the personalized bookstore included a main menu on the left-hand side and a taxonomy listing of six categories. The six categories were accounting, finance, economics, IS, marketing, and management (Figure 5a). The order of the icons for the six categories was randomized to minimize bias. In addition to these categories, the home page presented a set of six (personalized or random) items at the bottom of the window. The same set of items was repeated on every page in the same area of the window. By clicking on categories or on one of the books, participants would reach a page that showed the details of a book (Figure 5b). Next to those details were two buttons: "Sample" and "Add to Basket." When participants clicked on the "Sample" button, a detailed description of and customers' comments on the selected book were presented. They could sample a book any number of times.

After sampling a book, the participants were instructed to complete a thought-listing measure[4] by inputting the thoughts elicited by the book into the textboxes (Figure 5b). They could also evaluate a sampled book on a nine-point Likert scale (in which 1 corresponded to "strongly dislike" and 9 to "strongly like") and select any number of favorite books to add to their basket. This evaluation score would be used when the system generated personalized recommendations for return visits. Clicking on the "Proceed to Download" button displayed the books inside the basket from which the participant was required to choose one as his or her item selection.

Measures

The lab study tracked two types of measures: perceptual and behavioral. Whenever possible, perceptual measures were adapted from existing validated scales. The behavioral measures were captured in the course of a participant's process of book selection. The measures, along with the scale anchors and sources, are presented in Appendix B. Eight variables—quality of personalization, variation of personalized items, attitude persistence, attitude confidence, depth of processing, subsequent breadth of sampling, cumulative breadth of sampling, and actual selection from the personalization agent—were related to our six hypotheses.

[4]The thought-listing technique is a form of protocol analysis to capture depth of processing. It has been used in prior ELM studies (e.g., Cacioppo and Petty 1981; Petty and Cacioppo 1986a; Petty et al. 1993) and has proven to be an important tool in tracking the amount of cognitive activity involved in persuasion (Petty and Cacioppo 1986a).

First, we examined the four perceptual variables. *Quality of personalization* was a participant's perception of the extent that personalized recommendations matched his or her needs. We captured this variable with three questions in each pre-task questionnaire. *Variation of personalized items* was the variance in a participant's perception of the quality of individual personalized recommendations. To capture this variable, we asked the participant to score each personalized recommendation that he or she sampled. We calculated the variance of these scores to form variation of personalized items for that participant. To measure *attitude persistence*, we asked each participant in both the pre-task and the post-task questionnaires of each session to report his or her attitude (valence) toward the personalization agent. Attitude persistence was then calculated as the inverse of the absolute difference in the valence of a participant's attitude toward the personalization agent in the post-task questionnaire of the previous visit and the valence of his or her attitude in the pre-task questionnaire of the current visit. As the participant did not interact with the personalization agent between sessions, this captured attitude persistence. Finally, to measure *attitude confidence*, following the questions eliciting the valence of a user's attitude toward the personalization agent, we asked two additional questions regarding the user's confidence in his or her attitude (valence) toward the agent.

Next, we examined the four behavioral variables. *Depth of processing* was operationalized as the average number of text comments that a user wrote to describe his or her thoughts relating to a sampled item. *Subsequent breadth of sampling* was operationalized through sampling from the personalization agent as the number of personalized books that a participant sampled in the log-on session on the website subsequent to the current log-on session. Clicking on the "Preview" button to view the book description is what we refer to as sampling. We counted only the sampling of *distinct* items on each visit because our theoretical development of the definition of confidence and its relationship to cumulative sampling is based on CST, in which item sampling is an act of search that adds new information, thus there is no meaning in clicking on the same item again. Similarly, *cumulative breadth of sampling* was operationalized in terms of the number of previews of distinct personalized items from the first session to the current session. *Actual selection* was a binary variable—1 referred to a selection of a personalized item as a participant's item selection and 0 referred to otherwise.

Seven variables in our model were not involved in any hypothesis testing. Two of them, *perceived usefulness* and *attitude valence*, came from the combined ELM-TAM (Figure 4). Five of these (*age*, *gender*, *need for cognition* (NFC), *motivation*, and *ability*) were control variables. The questionnaire items for these variables were shown in Appendix B. We included these control variables for the following reasons: ELM theory states that a person's motivation and ability influences his or her depth of processing. Breadth of search does not exist as a construct in the original ELM. Since both depth of processing and breadth of search capture the amount of cognitive effort invested by a person to make a decision, we anticipated that a person's motivation and ability would also influence his or her cumulative breadth of search. We included gender and age as control variables, as prior studies indicated that they influenced online users' intentions to use a system (e.g., Venkatesh et al. 2003). Finally, we controlled the effects of NFC on item selection. According to ELM theory, NFC moderates the attitude argument quality-evaluation link (Petty and Cacioppo 1986b, p.107) and the attitude valence-behavior link (Petty and Cacioppo 1986a, p. 180). Hence, we included the moderating effect of NFC on these two relationships.

The research model involves a number of constructs and relationships that are defined over time. These ideas are summarized in light of our operationalized measures, so that the temporal logic of the research model is clear. ELM theory provides the idea that the extent of elaboration—that is, the degree to which the person engages in central-route processing—results in attitude persistence. We operationalize attitude persistence at time period t as the inverse of the change in attitude valence that occurs between period t and period $t - 1$. Since we measure the user's attitude valence at the beginning and end of each period, we are able to specifically operationalize persistence at time t as the change in attitude valence between the end of period $t - 1$ and the beginning of period t, so that there is no intervening activity at the website. Processing depth during period $t - 1$ is predicted to make the resulting attitude persist into time t. Next, based on CST, we theorize that users who have sampled more items in total will have greater confidence in their attitude. We predict that the total amount of sampling, from the beginning through period t, will influence attitude confidence at the end of period t. We also hypothesize a moderating effect of persistence on this link, whereby the effect of cumulative sampling on confidence at the end of period t depends on the extent to which past sampling was still exerting any effect at the time the user entered period t. Finally, confidence at the end of period t is predicted to reduce the amount of sampling during period $t + 1$. Other relationships and variables do not involve a temporal aspect.

The full model defines a set of causal connections that are played out over a period of three sessions. Assuming that the bulk of constructs are measured at session t, depth of processing that influences attitude persistence is measured at $t - 1$ and subsequent breadth of sampling is measured at $t + 1$. Thus, the model defines a set of structural relationships that play out over three periods. We have four sessions of data, which allows us to test the model on two separate three-session periods, Sessions 1–3 and Sessions 2–4. Here, we report results for Sessions 2–4, which we view as more representative because users were well acquainted with the system by these latter sessions.

Participants and Descriptive Statistics

We distributed flyers on campus to recruit undergraduate students in the School of Business to participate in our lab study. We recruited 379 undergraduate students (153 males and 226 females, average age = 19). On average, these 379 participants spent 3.5 hours per day Internet browsing. All of them had online shopping experience. Tables 2 and 3 present the descriptive findings of our behavioral and perceptual variables respectively. As seen in Table 2, there was a consistent pattern of decline in user activities with the personalization agent—depth of processing of personalized recommendations declined from 14.55 to 1.11, breadth of sampling from the personalization agent declined from 2.87 to 0.71, and the likelihood of selecting a personalized item as item selection declined from 53 to 41 percent.[5]

Construct Validation and Tests of Common Method Bias

Mplus 6.0, a covariance-based structural equation modeling technique, was used to analyze the data. Appendix C presents the results of construct validation for the lab study. We analyzed and validated the constructs using two sequential methods: item culling and confirmatory factor analysis (CFA). First, for variable purification, we took item-culling steps, as recommended by Churchill (1979). As a first item-culling step, we tested the model variables for univariate and multivariate threats to normality. Variation of personalized items had the largest values of skewness (2.43) and kurtosis (7.62), but still not exceeding the < 3.0 standard for acceptable skewness and the < 10.0 standard for acceptable kurtosis (Kline 2010). Thus, we concluded that no variable exhibited significant departure from normality. As a second item-culling step, we performed a principal components factor analysis to check whether those constructs with multiple items—quality of personalization, perceived usefulness, attitude valence, attitude confidence, attitude persistence, NFC (a control variable), motivation (a control variable) and ability (a control variable)—met the two criteria: (1) items loading more on their own construct than on another construct, and (2) items loading at least 0.70 on their own construct. Table C1 confirms that all items passed the second item-culling step.

Following that, a CFA was conducted. CFA tests how well the proposed factor structure fits the data. Fit is evaluated using the RMSEA, CFI, TLI and SRMR, per Kline (2010). The results suggested that the proposed factor structure has a reasonably good fit with the data (CFI = 0.93, TLI = 0.94, SRMR = 0.08, and RMSEA = 0.063). We also examined construct reliabilities, convergent validities of measures associated with individual constructs, and discriminant validities between constructs. First, we assessed construct reliabilities. The reliabilities of the discussed constructs are presented in Table C2. As all reliabilities were above the recommended threshold of 0.70, the first criterion was met. Second, we assessed convergent validity, which involved two steps. In the first step, we confirmed that the average variance extracted (AVE) for all constructs was higher than the recommended threshold of 0.5 (Table C2). In the second step, we checked all item loadings to their corresponding constructs and confirmed that all loadings were significant at the $p < 0.01$ level. Thus, convergent validity was reasonably satisfactory. Third, we assessed discriminant validity, which involved two steps. In the first step, we fixed the correlation between construct pairs at 1.0 and then reestimating the modified model (Segars and Grover 1993). Significant χ^2 differences suggest discriminant validity. We tested all 45 pairwise combinations among the 10 constructs, finding all the χ^2 differences to be significant at $p < 0.01$. In the second step, we checked whether the square roots of the AVE values were greater than the off-diagonal correlations. Table C2 showed the results of the second step. The two tests confirmed that discriminant validity was reasonably satisfactory.

Common method bias can threaten the validity of paths that link two variables that were measured in a single survey instrument. Consistent with the approach of Venkatesh et al. (2011), we conducted the Harman's one-factor test to evaluate the possibility of common method bias. In this test, if a substantial amount of common method variance (CMV) exists, a single factor will emerge from the factor analysis or one general factor will account for the majority of the covariance in the independent and dependent variables (Podsakoff et al. 2003). Following Venkatesh et al. (2011), we conducted four

[5]The website contained only six recommendations and 10,000 stock items in the general catalogue. The probability of randomly selecting a personalized item is 6/10,006 = 0.06%. Hence, having a 41% to 53% likelihood of selecting a personalized item was considered as evidence that the personalization agent was effective.

Table 2. Descriptive Statistics of Behavioral Variables for the Lab Study (N = 379)

	Depth of processing of personalized items (mean [SD])	Breadth of sampling of personalized items (mean [SD])	Participants who chose a personalized item as item selection (%)
Session 1	14.55 [1.85]	2.87 [1.46]	53
Session 2	2.31 [1.95]	1.50 [1.34]	52
Session 3	1.97 [1.75]	0.72 [1.05]	49
Session 4	1.11 [1.39]	0.71 [0.62]	41

Table 3. Descriptive Statistics of Perceptual Variables for the Lab Study (N = 379)

Mean [SD]	Mot	Ability	Quality	Variation	PU	Valence	Conf	Persist	NFC
Session 1	3.67 [1.79]	4.58 [1.35]	6.83 [2.39]	2.59 [2.73]	5.37 [2.42]	5.51 [2.53]	4.85 [3.12]	Undefined	6.03 [2.20]
Session 2	3.59 [1.72]	4.49 [1.32]	6.79 [2.42]	2.37 [2.82]	5.46 [2.60]	5.24 [2.74]	5.13 [2.42]	5.00 [2.16]	
Session 3	3.65 [1.78]	4.52 [1.36]	6.81 [2.41]	2.48 [2.80]	5.44 [2.56]	5.33 [2.31]	5.62 [2.41]	5.00 [2.04]	
Session 4	3.68 [1.81]	4.56 [1.37]	6.76 [2.38]	2.43 [2.75]	5.38 [2.62]	5.40 [2.70]	6.53 [2.39]	5.54 [1.86]	

Note: SD = Standard Deviation; Mot = Motivation; Ability = Ability; Quality = Quality of Personalized Items; Variation = Variation of Personalized Items; PU = Perceived Usefulness; Valence = Attitude Valence; Conf = Attitude Confidence; Persist = Attitude Persistence, NFC = Need for Cognition.

Harman's tests (i.e., one test for constructs measured at each logon session). The first factor accounted for 23 percent of the variance of constructs measured at session 1, for 25 percent at session 2, for 24 percent at session 3, and for 20 percent at session 4. In sum, these results indicate that the first factor does not account for the majority of the covariance in any of the tests, suggesting that common method bias is not a concern in our data set. As an additional test for CMV, we employed the marker variable technique (Lindell and Whitney 2001; Malhotra et al. 2006). Specifically, we chose the second-smallest positive correlation among the constructs, (i.e., 0.065, the correlation between motivation and attitude valence) as a conservative estimate of CMV to produce the CMV-adjusted correlation matrix (Lindell and Whitney 2001). Following Malhotra et al. (2006), we produced a CMV-adjusted correlation matrix and then used it to estimate CMV-adjusted path coefficients and explained variance. The results show that after controlling for the common marker, explained variance in the dependent variables decreases, but the drop is not substantial (i.e., 2 to 5 percent). In addition, the adjustment affected only two of the paths that can be attributed to common methods bias (i.e., paths linking two constructs measured by survey) and these are both control links in the lab study only, whose significance level changed to marginal. These results demonstrate the robustness of our findings to common method bias.

Hypothesis Testing

We ran a path analysis. As the endogenous variable (i.e., item selection) in our model was binary, we used "the CATEGORICAL option" (Muthén and Muthén 2008–2010, p. 33) in Mplus version 6.0 to specify that it was treated as binary in the model and its estimation. In addition, we used "the CENTERING = GRANDMEAN option"[6] (p. 495) to subtract the overall sample mean from each original variable, and "the XWITH command" (p. 71), which estimates a latent-variable interaction between two continuous latent variables. Figure 6 depicts the path analysis model for the lab study using data from Sessions 2–4. We followed the report of modification indices to include two additional paths: NFC ↔ motivation and attitude valence ⇢ subsequent breadth of sampling. The final model showed a CFI of 0.954 and a TLI

[6]Mean centering the predictor variables prior to creating interaction or product terms has two advantages: (1) mean centering alleviates problems of collinearity among the predictor variables that result from the nonessential collinearity among the main effects and their interaction term when one simply forms the product of the variables; (2) mean centering increases the interpretability of the estimates, as the coefficient for a mean-centered predictor may be more practically meaning than the same coefficient for the same predictor with an arbitrary zero point (Little et al. 2007; Marsh et al. 2004).

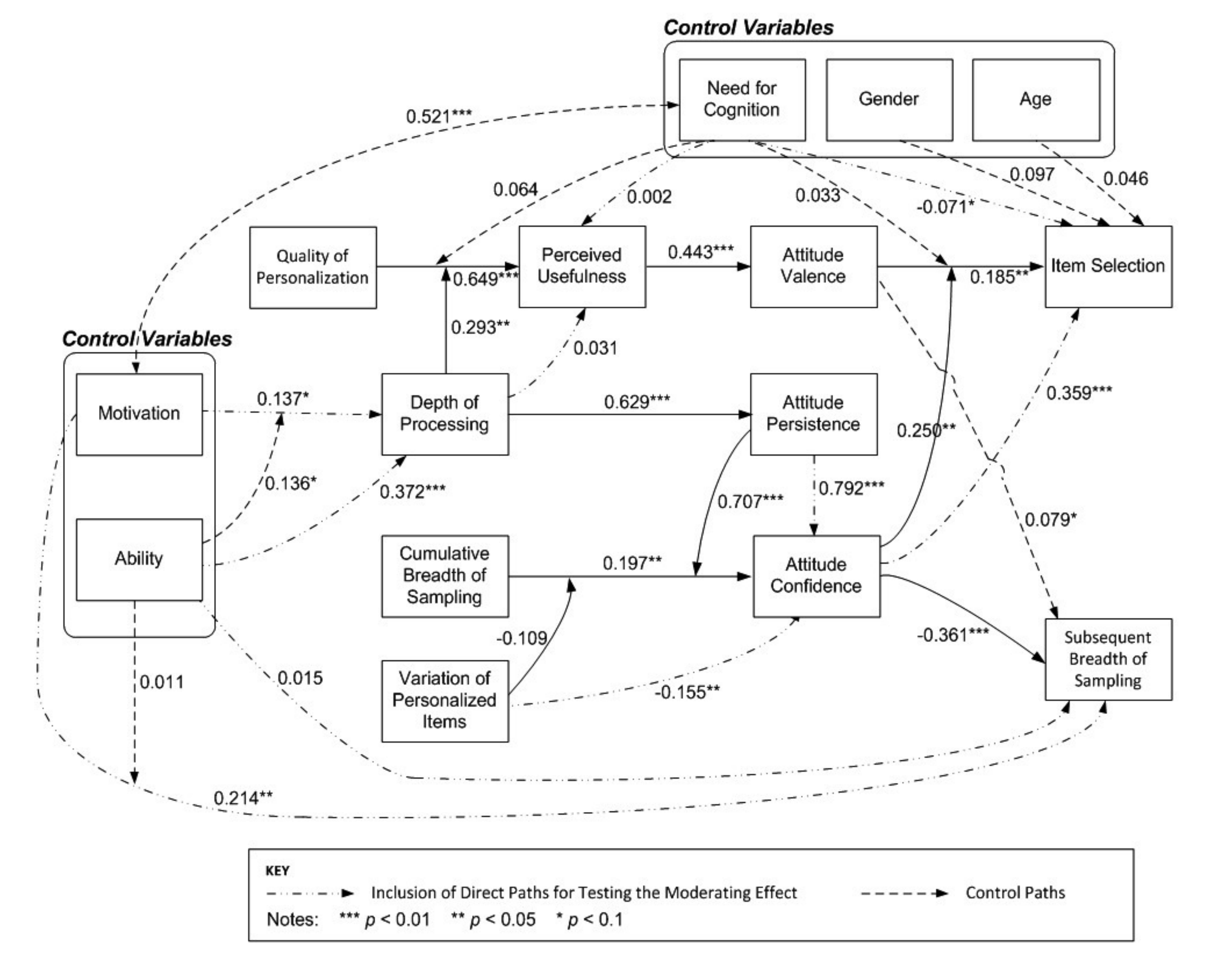


Figure 6. Path Analysis of the Lab Study (Sessions 2–4)

of 0.948, a weighted root-mean-square residual (WRMR)[7] of 0.82, and a RMSEA of 0.073. The CFI (greater than the cutoff of 0.95), TLI (greater than the cutoff of 0.95), WRMR (less than the cutoff of 0.9), and RMSEA (less than the cutoff of 0.08) were satisfactory, which demonstrated a good model fit. The R-squares of the dependent variables were satisfactory—0.199 for depth of processing, 0.523 for perceived usefulness, 0.952 for breadth of subsequent sampling, 0.645 for attitude confidence, 0.328 for attitude persistence, 0.447 for attitude valence, and 0.723 for item selection. Appendix D presents the path analysis using data from Sessions 1–3.

H1 examines the effect of depth of processing of personalized recommendations on persistence of a person's attitude toward the personalization agent. The positive coefficient ($\beta = 0.629$, $t = 9.069$, $p < 0.01$) indicates that when a participant processed personalized recommendations to a higher extent, they were more likely to form a persistent attitude. This positive effect was found to be significant, supporting H1.

H2 examines the effect of confidence of a person's attitude toward the personalization agent on his or her subsequent breadth of sampling from the personalization agent. We controlled the effect of attitude valence on subsequent breadth of sampling from the personalization agent. The negative coefficient ($\beta = -0.361$, $t = -2.943$, $p < 0.01$) for the path from attitude confidence to subsequent breadth of sampling con-

[7]WRMR was proposed by Muthén and Muthén (2008–2010). It is suitable for models with categorical outcomes.

firms the negative effect of attitude confidence on the amount of subsequent personalized sampling. This negative effect was found to be statistically significant, thus supporting H2.

H3, H4, and H5 consider the relationship between cumulative breadth of sampling from a personalization agent and confidence of a person's attitude toward the personalization agent. H3 focuses on the direct effect. The positive coefficient ($\beta = 0.197$, $t = 3.097$, $p < 0.05$) for the path from cumulative breadth of sampling to attitude confidence indicates that a person who had sampled more personalized items in his or her previous log-on sessions would form a more confident attitude. This positive effect was found to be statistically significant, supporting H3. H4 examines the moderating effect of variation of personalized items on the direct relationship specified in H3. The negative coefficient ($\beta = -0.109$, $t = -0.847$, $p > 0.1$) indicates that the more varied the personalized items were, the weaker the effect of cumulative breadth of sampling was on attitude confidence. Although the direction of the effect followed our prediction, the moderating effect was not found to be statistically significant, thus H4 is not supported. Finally, H5 examines the moderating effect of attitude persistence on the direct relationship specified in H3. The positive coefficient ($\beta = 0.707$, $t = 5.459$, $p < 0.01$) indicates that the more persistent an attitude was, the stronger the effect of cumulative breadth of sampling was on attitude confidence. The moderating effect of attitude persistence was found to be significant, so H5 is supported.

H6 examines how attitude confidence moderates the relationship between attitude valence and a person's item selection. Attitude valence ($\beta = 0.185$, $t = 1.965$, $p < 0.05$) exerted a positive effect on item selection, indicating that the participant selected a personalized item if he or she liked the personalization agent. The coefficient of the moderating effect of attitude confidence ($\beta = 0.250$, $t = 2.120$, $p < 0.05$) on this relationship was also positive. This implies that the effect of attitude valence on the participant's item selection was stronger when he or she held a more confident attitude, thus H6 is supported.

Field Study (Study 2)

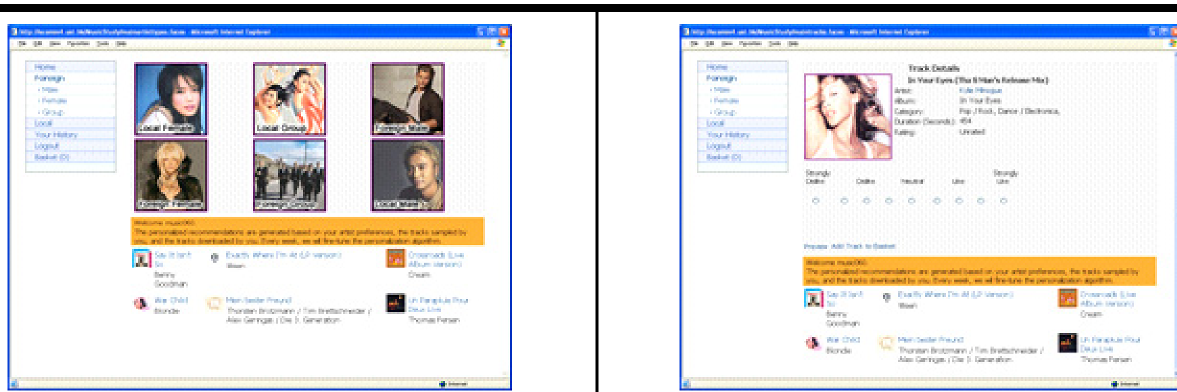
In the field study, we collaborated with the largest digital music provider in the Asia Pacific region to develop a personalized music website and invited their registered members to be our participants. During a six-month period, participants visited our personalized music website multiple times to view music track details, listen to track previews, and download tracks. We chose digital music as our study context because digital music is an experience good in which user clicks are particularly meaningful in terms of inspecting an item and evaluating the personalization agent (Hauser and Wernerfelt 1990; Klein 1998). We conducted a field study to increase the external validity of our findings by providing a natural shopping environment to real shoppers to select the products that they would actually use.

Setup and Procedures

During registration, participants completed a questionnaire designed to collect demographic information and chose and ranked their three favorite artists from a list of 50. Subsequently, they were provided with four tokens for digital music downloads. Once per week, they could enter our website, listen to any number of music previews, and download one as their item selection. After downloading, participants could update their music preferences. The procedures were similar to those for the lab study except that participants did not see a short task scenario and they downloaded a music track based on their own preferences; they were not asked to write down text comments after each sampling; and they received the chosen music files (in *.wma format), which were transferred to their client computers after each session. These differences made the music download environment more natural for the purpose of external validity.

Figures 7a and b show the interfaces of our personalized music website. Our database had 200,000 music tracks from 6,670 artists. There were roughly 30 tracks per artist, although the more popular artists had significantly more tracks. As in the lab study, half of the participants received good recommendations while the other half received poor recommendations. To generate good recommendations, our system ranked music tracks according to album sales, billboard popularity, and participants' feedback, and put the top half of the music tracks into a pool for consideration. For each participant on each visit, the system randomly chose two tracks from this pool for each of that participant's three preferred artists to generate six recommendations. Participants could update their music preferences after each download. In this manner, the same participant would see mostly new personalized recommendations on each visit. To generate poor recommendations, our system randomly drew six items from the pool.

Prior to the main study, we conducted two pilot tests with 35 participants to check the performance of the music website. All pilot participants could complete the entire process of one selection session within 15 minutes and confirmed that the music selection process was smooth.



(a) Home Page of the Music Website

(b) Web Page for Music Track Sampling

Figure 7. Interfaces for the Personalized Music Website

User Interface Design

The design of the experimental website for the field study was identical to that for the lab study, except that the product items were music tracks rather than books; the six categories on the home page of the experimental website were local male artists, local female artists, local groups, international male artists, international female artists, and international groups; and, unlike the book sampling web page (Figure 5b), the music track sampling web page (Figure 7b) did not provide space for participants to write text comments to describe their thoughts about the sampled music track.

Measures

The measures used in Study 2 were identical to those used in Study 1, except that we did not measure depth of processing, ability (a control variable), or motivation (a control variable). Appendix B presents the operationalization and the measures for each construct. As with the lab study, the field study provided us with data for four sessions, which allowed us to test the model on two separate three-session periods (Sessions 1–3 and Sessions 2–4). Here, we report results for Sessions 2–4.

Participants and Descriptive Statistics

The digital music content provider sent e-mail invitations to its registered members and announced our study in its monthly newsletter. Potential participants clicked on a hyperlink to start the registration process. We recruited 205 registered members (115 males and 90 females, average age = 28), all of whom were active consumers who had logged onto the digital music provider's regular website at least twice in the previous 12 months. Tables 4 and 5 present the descriptive findings for the behavioral and the perceptual variables respectively. Table 4 shows that there was a consistent pattern of decline in user activities with the personalization agent—breadth of sampling from the personalization agent declined from 2.31 to 0.33 and the likelihood of selecting a personalized item as an item selection declined from 31 to 2 percent.[8]

Construct Validation and Test of Common Method Bias

Appendix E presents the results of construct validation for the field study. We followed the same item-culling procedures in the previous section. We first tested the model variables for univariate and multivariate threats to normality and confirmed that no variable exhibited significant departure from normality. Then, we performed a principal components factor analysis on those constructs with multiple items—quality of personalization, perceived usefulness, attitude valence, attitude confidence, attitude persistence, and NFC (a control variable). Table E1 shows that all items load more on their own construct than on another construct. Five items (PU5, NFC2, NFC4, NFC5, and NFC6) had a loading smaller than the recommended threshold of 0.70. However, as this was a field study involving participants completing the study in a less controlled environment, and since four of those five items come from a control variable (NFC), and all items load more

[8]The website contained only six recommendations and about 200,000 stock items in the general catalogue. The probability of randomly selecting a personalized item is 6/200,000 = 0.003%. Hence, having a 2–31% likelihood of selecting a personalized item was considered as evidence that the personalization agent was effective.

Table 4. Descriptive Statistics for the Field Study [Behavioral Variables] (N = 205)		
	Breadth of sampling of personalized items (mean [SD])	**Participants who chose a personalized item as item selection (%)**
Session 1	2.31 [1.49]	31
Session 2	1.07 [1.02]	9
Session 3	0.72 [0.69]	9
Session 4	0.33 [0.41]	2

Table 5. Descriptive Statistics for the Field Study [Perceptual Variables] (N = 205)							
(mean [SD])	**Quality**	**Variation**	**PU**	**Valence**	**Confidence**	**Persist**	**Need for Cognition**
Session 1	6.75 [1.58]	1.91 [1.31]	6.27 [1.50]	6.37 [2.71]	6.51 [2.85]	Undefined	7.40 [1.29]
Session 2	6.70 [1.47]	2.33 [1.32]	6.28 [1.53]	6.32 [2.93]	7.11 [2.57]	4.58 [2.39]	
Session 3	6.67 [1.43]	2.03 [1.46]	6.19 [1.68]	6.31 [2.69]	7.67 [2.53]	5.01 [2.04]	
Session 4	6.54 [1.60]	1.92 [1.44]	6.14 [1.63]	6.09 [2.77]	7.96 [2.31]	5.46 [1.86]	

Note: SD = Standard Deviation. Quality = Quality of Personalization; Variation = Variation of Personalized Items; PU = Perceived Usefulness; Valence = Attitude Valence; Conf = Attitude Confidence; Persist = Attitude Persistence, NFC = Need for Cognition.

on their own construct than any other, we considered all constructs to have passed the item-culling criteria.

Following that, we conducted a CFA and the results suggest that the proposed factor structure has a good fit with the data (CFI = 0.92, TLI = 0.93, SRMR = 0.081, and RMSEA = 0.06). We also examined construct reliabilities, convergent validities, and discriminant validities. First, we assessed construct reliabilities. The reliabilities of the discussed constructs are presented in Table E2. As all reliabilities were above the recommended threshold of 0.70, the first criterion was met. Second, we assessed convergent validity, which involved two steps. In the first step, we confirmed that the AVE for all constructs was higher than the recommended threshold of 0.5 (Table E2). In the second step, we checked all item loadings to their corresponding constructs and confirmed that all loadings were significant at the $p < 0.05$ level. Thus, convergent validity was reasonably satisfactory. Third, we assessed discriminant validity, which involved two steps. In the first step, we fixed the correlation between construct pairs at 1.0 and then reestimating the modified model (Segars and Grover 1993). Significant χ^2 differences suggest discriminant validity. We tested all 36 pairwise combinations among the nine constructs, finding all the χ^2 differences to be significant at $p < 0.05$. In the second step, we checked whether the square roots of the AVE values were greater than the off-diagonal correlations. Table E2 showed the results of the second step. The two tests confirmed that discriminant validity was reasonably satisfactory.

We also conducted the Harman's one-factor test to evaluate the possibility of common method bias. Specifically, we conducted four Harman's tests, one test for constructs measured at each logon session. The first factor accounted for 17 percent of the variance for data collected at session 1, for 19 percent at session 2, for 17 percent at session 3, and for 15 percent at session 4. These results indicate that the first factor does not account for the majority of the covariance in any of the tests, suggesting that common method bias is not a concern in our data set. As an additional test for CMV, we employed the marker variable technique (Lindell and Whitney 2001; Malhotra et al. 2006) to account for common method bias and then test the hypotheses based on the corrected correlations. The results show that after controlling for CMV effects, the explained variances in the dependent variables decrease, but the drop is not substantial (i.e., 2–6%). The path coefficients are mostly consistent with those that were found without the CMV adjustment. These results demonstrate the robustness and the validity of our findings and limit the threat of common method bias.

Hypothesis Testing

Figure 8 depicts the path analysis result for the field study using data from Sessions 2–4. We followed the report of modification indices to include an additional path: cumulative breadth of sampling → subsequent breadth of sampling. The final model showed a CFI of 0.957 and a TLI of 0.958, a

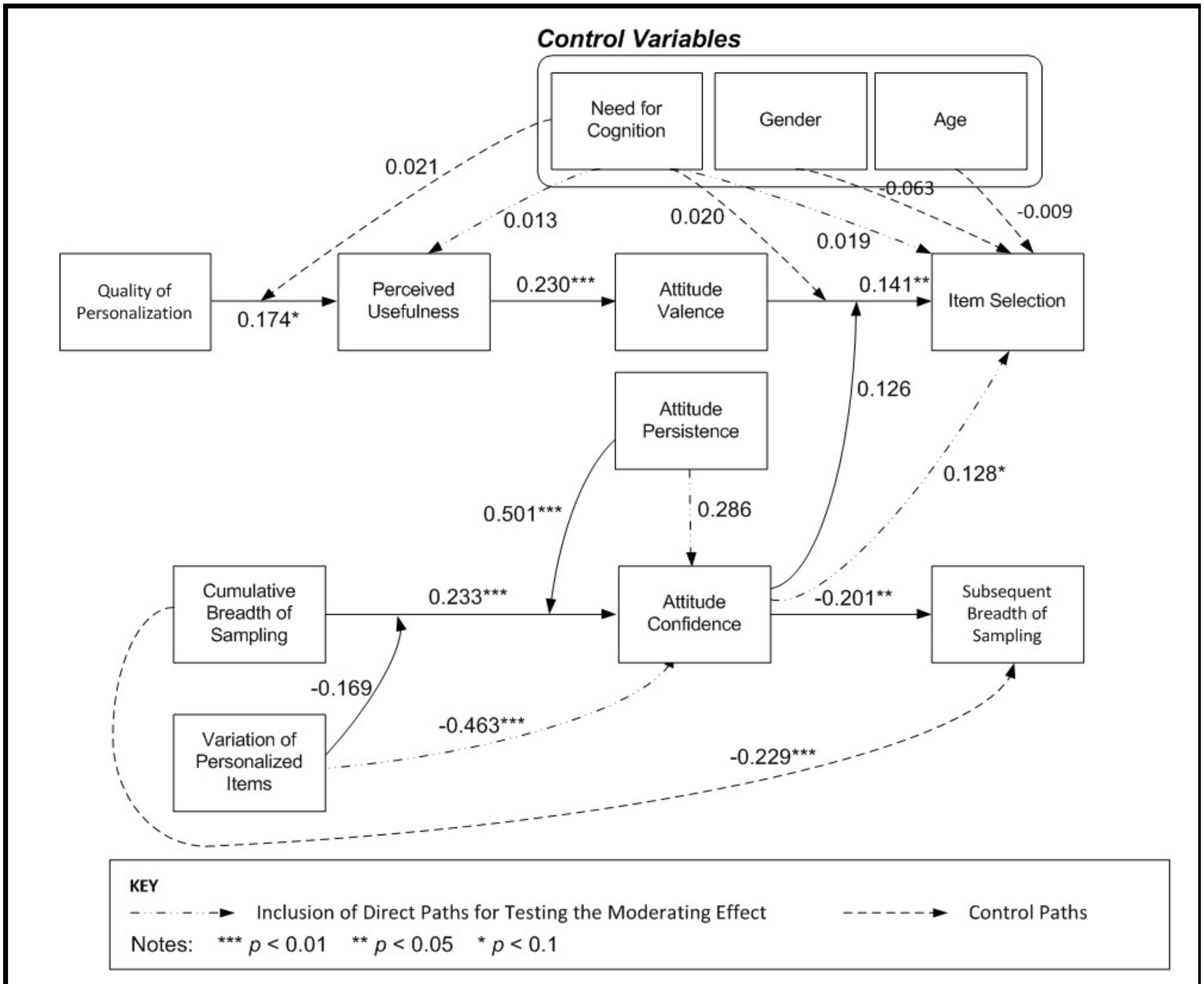


Figure 8. Path Analysis of the Field Study (Sessions 2–4)

WRMR of 0.80, and a RMSEA of 0.030. The CFI (greater than the cutoff of 0.95), TLI (greater than the cutoff of 0.95), WRMR (less than the cutoff of 0.9), and RMSEA (less than the cutoff of 0.08) were satisfactory, demonstrating a good model fit. The R-squares of the dependent variables were satisfactory—0.200 for perceived usefulness, 0.458 for subsequent breadth of sampling, 0.576 for attitude confidence, 0.132 for attitude valence, and 0.115 for item selection. Appendix F presents the path analysis using data for Sessions 1–3.

Since the field study was designed to enhance external validity of our findings, we did not include textboxes for participants to list their thoughts after sampling a digital music selection. Hence, depth of processing was not measured and H1 could not be tested. Thus, we began with H2. H2 examines the effect of confidence of a person's attitude toward the personalization agent on his or her subsequent breadth of sampling from the personalization agent. The negative coefficient ($\beta = -0.201$, $t = 2.418$, $p < 0.05$) for the path from attitude confidence to subsequent breadth of sampling indicates that attitude confidence reduced the subsequent personalized sampling. This negative effect was found to be statistically significant, thus H2 is supported.

H3, H4, and H5 examine at the relationship between cumulative breadth of sampling from a personalization agent and attitude confidence. H3 focuses on the direct effect. The positive coefficient ($\beta = 0.233$, $t = 6.125$, $p < 0.01$) for the path from cumulative breadth of personalized sampling to attitude confidence indicates that a person who had sampled more personalized items in his or her previous log-on sessions would form a more confident attitude. As this effect was found statistically significant, this indicates that H3 is supported. Next, H4 examines the moderating effect of variation of personalized items on the relationship specified in H3. The negative coefficient ($\beta = -0.169$, $t = -1.141$, $p > 0.1$) indicates that the more varied the personalized items were, the weaker the effect of cumulative breadth of personalized sampling was on attitude confidence. Although the direction of the effect followed our prediction, this effect was not found to be statistically significant, so H4 is not supported. Finally, H5 examines the moderating effect of attitude persistence on the relationship specified in H3. The positive coefficient ($\beta = 0.501$, $t = 5.966$, $p < 0.01$) indicates that the more persistent an attitude was, the stronger the effect of cumulative breadth of personalized sampling was on attitude confidence. Thus, as the moderating effect of attitude persistence was found significant, H5 is supported.

H6 examines how attitude confidence moderates the relationship between attitude valence and a person's item selection. Attitude valence ($\beta = 0.141$, $t = 2.590$, $p < 0.05$) exerted a positive effect on item selection. This indicates that the person would select a personalized item if he or she liked the recommendations by the personalization agent. Although the coefficient of the moderating effect of attitude confidence ($\beta = 0.126$, $t = 0.693$, $p > 0.1$) on this relationship matched our prediction, it was not significant, thus H6 is not supported.

Discussion

Table 6 summarizes our findings. We set out to develop a broad understanding of attitude formation and two aspects of behavior—item sampling and item selection—with a personalization agent. To this end, we synthesized two complementary theories and applied them to the question of web personalization. We conducted a lab study and a field study to test the six hypotheses. Our approach promised a more complete understanding of how web personalization influences user attitude and behaviors.

Hypotheses 1–5 showed consistent results across the two studies. H6 was significant in the lab study but not in the field study. One possible reason for this is that the website in the lab study contained 10,000 books whereas the website in the field study contained 200,000 music tracks. Since there were so many alternatives available to participants in the field study, a much higher attitude confidence might have been required to exert an influential moderating effect between attitude valence and a participant's item selection.

The data also showed two significant predictors of item selection that we had not hypothesized: NFC exerted a direct negative effect on the person's actual selection of a personalized item in the lab study, and attitude confidence exerted a positive direct effect on item selection in both the lab and field studies. In ELM theory, people with a high NFC have a higher resistance to persuasion, but this should result in NFC moderating the link to attitude valence, not directly affecting item selection behavior. Similarly, ELM models attitude confidence to moderate the link from attitude (i.e. valence) to behavior (Cacioppo and Petty 1982), but not to have a direct effect on behavior. The two effects that were not hypothesized seem to have a common underlying logic, according to which a consumer is more likely to select one of the recommended items if he/she has either less of a need, or greater ability, to confidently understand or assess the agent. These unanticipated effects warrant further study.

Theoretical Contributions

This research contributes to the literature in several ways. First, we introduced CST to extend ELM, an existing theory used in personalization research (Tam and Ho 2005). Our model conforms to a combined ELM-TAM structure, as extended by Bhattacherjee and Sanford (2006), but extends it to address questions related to web personalization. Our model distinguishes between two kinds of usage—item sampling and item selection—which characterize usage of a personalization agent and correspond to informational usage and transactional usage in the e-commerce literature (Jansen et al. 2008). Thus, our research contributes a predictive model of behavioral outcomes in the context of personalization.

Second, our model relates three aspects of attitude—valence, persistence, and confidence—to two behavioral outcomes, item sampling and selection. The combination in a single model of a multidimensional definition of *attitudes* and a multidimensional definition of *usage* provides a newly enriched theoretical appreciation of the attitude–behavior link. The logic of the resulting model intuitively connects attitude formation, usage of a website's informational functions, and usage of its transactional functions. The overall logic is that users inspect information that the system provides; then, based partly on that experience, they develop an attitude toward the system; in turn, this attitude affects both the extent to which they elicit further information and whether they exe-

Table 6. Summary of the Findings

Hypotheses	Lab	Field
H1: Depth of processing has a positive effect on the persistence of attitude that users form toward the personalization agent.	Supported	–
H2: Confidence in one's attitude toward the personalization agent has a negative effect on subsequent breadth of sampling from the personalization agent.	Supported	Supported
H3: Cumulative breadth of sampling from the personalization agent positively influences confidence in one's attitude toward the personalization agent.	Supported	Supported
H4: Item variance negatively moderates the positive effect of cumulative sampling breadth on attitude confidence.	Not supported	Not supported
H5: Attitude persistence moderates the effect of cumulative breadth of sampling from the personalization agent on attitude confidence.	Supported	Supported
H6: Attitude confidence moderates the relationship between attitude valence toward a personalization agent and actual selection from the agent.	Supported	Not supported

cute a system-enabled purchase. This same structure may apply equally to other information systems besides personalization agents, especially e-commerce systems, many of which provide both informational and transactional functions. Our model provides a detailed map of the relationships between attitudes and their behavioral outcomes.

Third, our model synthesizes two theories, the ELM and CST, in a manner that naturally completes each one. Indeed, each of two original theories includes an undeveloped "placeholder" for the other: CST assumes a simple rational model of evaluation of the item source, which ELM extends to be more psychologically valid by considering different degrees of processing depth, the possibility of forgetting, and other psychological factors. In the case of the ELM, valence of attitudes are explicitly modeled as being based on individual items that have been encountered, but the theory is mute on how those recommendations came to be inspected in the first place; CST extends this by incorporating the user's decision of how many personalized recommendations to inspect. In this manner, the two theories are extended in natural ways that follow directly from their original outlines, yielding a naturally integrated model of the interplay between information use and attitudes.

Finally, our research also enriches our understanding of attitude formation and the attitude–behavior relationship in the longitudinal dimension. The model's two temporal variables—attitude persistence and cumulative sampling—correspond to two distinct operative aspects of the passage of time. The first aspect is the passage of clock time *per se*. On this dimension, the two theories have different perspectives. CST makes the assumption common to all rational theories of learning that once something is learned, it is never forgotten; therefore, the mere passage of time has no significance. In contrast, in considering the factors that influence attitude persistence, the ELM implicitly acknowledges the possibility of forgetting. Our model adopts the more psychologically valid and general assumption of the ELM, and therefore incorporates a role for attitude persistence. The second operative aspect of time is the amount of sampling that has already been done. On this aspect, the ELM and CST have similar perspectives. ELM research has considered the number of times a user has seen the same information item (e.g., advertisements), while CST models the more relevant effect of the number of different information items that have been seen thus far on attitude confidence. By incorporating the effects of clock time and cumulative sampling, our model considers both operative aspects of time on attitude formation and the attitude–behavior link in personalization agents.

Practical and Managerial Implications

The literature on personalization enumerates a series of possible benefits to an online merchant (Murthi and Sarkar 2003). These include sales revenue through upselling and advertising revenue through user activity on the website. Upselling, sometimes called second-degree price discrimination or product line versioning, occurs when different consumers buy vertically differentiated versions of a product (such as basic versus premium). It is directly supported by personalization, which can anticipate and recommend for each consumer the highest level of product that he or she might purchase. Advertising is directly supported when consumers show interest by clicking on the recommended items, regardless of whether they ultimately purchase them. Our research indicates that the two benefits may conflict, thereby highlighting the managerial imperative to prioritize among them based on the business' goals in deploying the personalization agent (Silver 1990, 1991). In particular, attitude confidence has the dual effect of tightening the link between attitude valence and item selection while simultaneously leading to decreased item sampling. Therefore, an online merchant that prioritizes upselling should wish to enhance attitude confidence, while an online merchant interested in advertising revenue should wish to mitigate it.

Beyond showing the need for clear prioritization of business goals, our model indicates possible ways that an online merchant can further them. Merchants that are chiefly interested in maximizing user clicks may wish to limit attitude confidence. Our model indicates that this can be accomplished in two ways. One way is through greater variety of personalized recommendations. We had predicted that greater item variance would negatively moderate the increase in confidence that comes from sampling. Although this *moderating* effect is not supported by the data, both Figure 6 and Figure 8 indicate a significant *direct* effect of item variance on attitude confidence. Our practical conclusion is that online merchants whose business priorities favor increased user clicks (i.e., those who prioritize advertising revenue) may wish to deploy algorithms that generate more varied recommendations. The second means of mitigating attitude confidence is related to attitude persistence. We predicted and empirically confirmed that lower attitude *persistence* negatively moderates the increase in attitude confidence that comes from sampling. As such, online merchants who prioritize user clicks may wish to present personalized recommendations only during intermittent visits or only after a fixed amount of time, when attitudes have partly faded.

For merchants whose main purpose in deploying the personalization technology is to drive sales by means such as upselling, the model prescribes the reverse choices (i.e., less variety) and presenting recommendations every time the user visits the site. However, this assumes a user with a positive attitude toward the personalization agent. If a user has a negative attitude valence, then even these merchants should seek to undermine the user's confidence in his/her (negative) attitude. Therefore, ideally, merchants focused on sales and who wish to fully exploit the implications of our model, should adopt two different strategies: one toward online users with a positive attitude and one toward those with a negative attitude. This would require the merchant to detect a user's attitude valence. One possible surrogate for a positive attitude is item selection in previous visits, with customers who selected a personalized recommendation presumed to hold a more positive attitude toward the personalization agent. For those who did not select a personalized recommendation, the model shows that this may reflect either a lower attitude valence or a lower attitude confidence; a one-item survey may suffice to distinguish between these.

So far, our discussion of practical implications assumes a business that is selling the merchandise of only one firm (i.e., products of one brand) on its own website. However, for retailers who carry products from many firms, the trade-off that our model shows between advertising and sales (and between item sampling and selection) becomes a conflict of interest between the firms and the online retailer. The brands are interested in item selection; each brand wants the consumer to select its product. By contrast, among products of comparable price, the retailer does not have any inherent stake in which brand a consumer selects. On the other hand, the retailer is interested in user clicks, which bring advertising revenue and which indicate an engaging shopping experience. Third-party personalization services such as RichRelevance attempt to provide win–win cooperation between the retailer and firms. Both the retailer and brands register for the personalization service, which analyzes consumers' clicks on the retailer's site, chooses firms' products that match each consumer's interests, and delivers them to the retail website as personalized recommendations. As an example, Target.com sells televisions by Philips, Samsung, and other firms, and has a contract with RichRelevance. If any of those television brands registers for RichRelevance's service, RichRelevance's personalization agent will consider recommending that brand's products to appropriate Target.com consumers. However, as our research indicates, there is a practical conflict of interest between the retailer and firms. The retailer benefits from item sampling that signifies consumer engagement and generates advertising revenue, while the firms benefit from item selection, and these different goals lead them to prefer different implementation details, as described above. With regard to previous consumer-related technologies such as universal product codes and electronic data interchange, Clemons and Row (1993) showed that the inherent conflicts of the brand–retailer relationship limit the ability of an information system to effect real interfirm coordination. Relatedly, our research portends the possibility that the conflicting interests between the retailer and firms may play itself out in the personalization sphere, with the two sides pushing for different implementation details that favor item sampling or item selection, respectively.

Future Research and Limitations

The integration of the ELM and CST enables IS researchers to examine the effects of web users' sampling breadth and processing depth on subsequent item sampling and selection. The integrated ELM-CST model is not limited to the examination of web personalization—a fairly direct extension of the model is application to social recommendations, as opposed to the automated recommendations considered here.

For instance, when a consumer reads the comments of past users of a given product, the ELM-CST model can predict how the number of comments the consumer has seen, combined with the extent of his or her cognitive processing, will influence the likelihood that he or she will both continue reading more comments and select the given item. Open research questions include how the effects differ when the items are recommended by fellow shoppers as opposed to a recommendation system. The framework can also be applied and extended to address marketing issues such as the effects of word-of-mouth (WOM) on customers' brand decisions. Customers receive positive or negative WOM information on a brand and the number of WOM messages they receive and the extent of processing can be modeled within this framework to influence both their brand decision and inclination to seek out additional messages.

Further, within IS theory, our model complements system adoption and continuance models. TAM-based adoption models describe the effects of users' perceptions on their adoption decision; continuance models (Bhattacherjee 2001) describe the effect of attitude valence on intention to continue usage; while the ELM-CST model describes the effects of the amount of information and cognitive processing on the decision of how much more information to solicit within and across sessions, as well as whether the user is likely to act on that information. Many fundamental questions remain open. In particular, a more integrated theory is needed to predict the amount of information a user requests from the system, his or her intention to continue using the system, and the degree to which he or she uses the information that is received.

This research is not without its limitations. First, our setup allowed participants to select exactly one item per log-on session, and thus did not allow us to study the number of items purchased. Future research can use transaction data from online merchants to examine the effects of personalization on sales volume. Second, our sample frame may limit the generalizability of the findings. We used student participants in the lab study and the participants in the field study were registered members of the digital music provider, thus not new to the provider, although the website used in our research and the personalization agent were new to them. This may limit our findings in this study to the behavior of users who are familiar with the provider. Third, in the lab study, we captured participants' depth of processing by asking them to list their thoughts of sampled items. Although this measure is established in the ELM literature, the thought-listing method might affect behavior in a way that limits the generalizability of our results for H1. The field study did not use this (or any other) measure of processing depth, thereby reaffirming that the model's other hypothesized links are not specific to settings in which users list their thoughts. Still, future research regarding the effects of processing depth may aim to establish other, less obtrusive measures; for instance, one may use a person's browsing duration on a product page to approximate his or her depth of processing. Fourth, our first study used books and our second study used digital music as the shopping context. Both are experience goods. We chose to use experience goods partly because user clicks are particularly meaningful in such a setting. To examine the boundary condition of the applicability of the integrated ELM-CST model, our research model would need to be examined in the context of search goods.

Conclusion

In this research, we integrate the perspectives of the ELM and CST to form an integrated model of attitude formation and behavior toward a personalization agent. These two theories complement each other. The ELM models a user's depth of processing of personalized recommendations, whereas CST models a user's breadth of sampling from the personalization agent. Our integrated model illustrates how depth and breadth influence a user's attitude toward a personalization agent and item selection. From a practical view, the work sheds light on the effectiveness and limitations of web personalization from a business perspective. Personalization could offer a basis for generating revenue because users are generally willing to sample and select personalized items as their final choice, but the amount of personalized sampling diminishes with attitude confidence, while selection of a personalized item depends on it.

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RESEARCH ARTICLE

THE EFFECTS OF WEB PERSONALIZATION ON USER ATTITUDE AND BEHAVIOR: AN INTEGRATION OF THE ELABORATION LIKELIHOOD MODEL AND CONSUMER SEARCH THEORY

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Appendix A

Task Scenarios for the Lab Study

Scenario 1

Next week, you will have your first job interview. The job is being offered by a small firm. The firm provides no training, no medical benefits, and no travel allowance to its employees. The starting salary is A$30,000 per annum, below the average starting salary of a fresh graduate, i.e., A$50,000. Indeed, you do not care much about this job.

Your friends told you that the job interviewers might ask you a few questions relevant to your textbook knowledge of your major. You believe that reading a book about your major might improve your performance in the interview. You are now deciding which book on the subject of your major to purchase.

Scenario 2

Next month, you will have your final examinations. After calculating your average scores for each course, you are sure that you can get high distinctions in almost all courses. You have finished reviewing all lecture materials, all tutorial materials, and all textbooks. However, there are still four weeks before the examination. Since you have extra time available, you plan to buy a book about your major to do some extra preparation.

You are now deciding which book about your major to buy. The book should cover most of the important topics for courses about your major. Because of your limited budget, you can only purchase one book.

Scenario 3

You get a new job, that of a teaching assistant (a tutor) at the University of Canberra. In the winter break, you need to deliver tutorials on an introductory course about your major. There will be 10 students in each tutorial. You will be responsible for one tutorial group only. You understand that the lecturer may use your performance as a reference to decide whether you can continue your tutor position, but students do not evaluate tutorials. If you teach well, you may be able to get another contract for the summer break. That means, you can have an income of A$3,000 in December 2011.

To prepare tutorial materials, you plan to purchase a book that covers most of the important topics about your major. Remember that it is an introductory course. The University of Canberra will reimburse you for the book.

Scenario 4

Sara is a friend of your friend. You have known her for two weeks. Sara has just enrolled in the Bachelor of Commerce degree at the Australian National University. She is a lazy learner. Her family is rich, and thus, she does not care about her academic results. These days, Sara is considering her major in the College of Business and Economics. Somehow, she guesses that she may like your major and asks you what you think. Since you know that Sara does not care about her studies, you might not want to spend much time on her. Hence, you decide to buy a book related to your major and give it to her, saying that she can have a look at it and decide for herself. You are now deciding which book about your major to purchase for her.

Scenario 5

Next week, you will have your first job interview. You are very interested in this job, considering that it is for a large Australian firm. The firm provides its new employees with good training. The benefits of medical support and travel allowance are also good. The starting salary is high, A$80,000 per annum. It is well above the average starting salary of a fresh graduate, i.e., A$50,000.

Your friends told you that the job interviewers will thoroughly test you on your textbook knowledge of your major. You believe that in the coming week, it is critical for you to read a book about your major to improve your interview performance. You are now deciding which book to purchase about your major.

Scenario 6

Next month, you will have your final examinations. Since you have been sick for six weeks, you missed most of the lectures for all courses. Although you listened to the audio recording on Wattle, it did not help much. To make things worse, you did not perform well in some assessments. You had very poor marks in the assignments and failed the mid-term examinations of two courses. You plan to purchase a book about your major.

You are now deciding which book to buy. The book should cover most of the important topics for the courses in your major. The book content should be concise and precise. Due to your limited budget, you can only purchase one book.

Scenario 7

You have just gotten a new job, an associate lecturer position at the University of Canberra. In the winter break, you are going to deliver lectures on an introductory course about your major. There will be 100 students in each lecture, and there will be three streams. Altogether, you will have 300 students. You are very excited about this new job. You understand that your teaching performance is crucial. If you teach well, you will be able to obtain a long-term contract. This means that, in every summer or winter break, you can have an income of A$20,000. Your performance will be evaluated by students.

To prepare lecture materials, you plan to purchase a book that covers most of the important topics about your major. Remember that it is an introductory course. The University of Canberra will reimburse you for the book.

Scenario 8

Sara is your best friend. You have known her for 15 years. She has just enrolled in the Bachelor of Commerce degree at the Australian National University. Sara is a very keen, enthusiastic, and hard-working learner. These days, she is considering her major in the College of Business and Economics. It seems that Sara is very interested in your major. Sara would like to seek your advice. After talking to her several times, you believe that a book about your major can be very useful to her. You are now deciding which book to purchase for Sara.

Appendix B

Measures

All items were measured with nine-point scales. Most were anchored with strongly disagree (1) – strongly agree (9) unless noted with an asterisk (*) and described below.

For each variable, we provide a description of "Data from which session to be used in data analysis." As mentioned in the sections on the measures for Study 1 and for Study 2, given four logon sessions, there are two ways to test our model, using data from sessions 1 to 3, and data from sessions 2 to 4. In this appendix, we assume that the model is being tested on sessions 2–4. In this case, the bulk of variables are measured at—or up to—session 3, as appropriate, with depth of processing to predict attitude persistence measured during session 2, and subsequent breadth of sampling measured during session 4.

Quality of Personalization (Tam and Ho 2006)

Definition: A person's perception of the extent of matching of personalized items to his/her needs.
Nature of measures: Perceptual, to be captured in questionnaires.
Measures:

Study 1: ***The lab study***
Quality1: The book recommendations shown at the bottom of the window are personalized to my needs.
Quality2: The book recommendations displayed at the bottom of the window match my needs.
Quality3: The book recommendations are personalized to me.

Study 2: ***The field study***
Quality1: The song recommendations shown at the bottom of the window are personalized to my preferences.
Quality2: The song recommendations displayed at the bottom of the window match my preferences.
Quality3: The song recommendations are personalized to me.

When this variable was measured: In all pre-task (except session 1) and all post-task questionnaires, we used present tense for the questions in the pre-task questionnaire, and past tense for the questions in the post-task questionnaire.
Data from which session to be used in data analysis: Data from the pre-task questionnaire in session 3.

Variation of Personalized Items

Definition: The variance in a person's perception of the quality of individual personalized recommendations.
Nature of measures: Perceptual, to be captured in the course of navigation.
Measures: Participants scored sampled personalized items with a nine-point Likert scale (1 = strongly dislike, 9 = strongly like). We calculated variance of these scores for each participant to form this construct.
When this variable was measured: In all sessions.
Data from which session to be used in data analysis: Data from sessions 1 to 3.

Attitude Persistence (Petty and Krosnick 1995)
Definition: The extent to which a previously formed attitude endures over time. *Nature of measures:* Perceptual, to be calculated from data collected in questionnaires. *Measures:* The inverse of the absolute value of the difference between attitude valence reported in the post-task questionnaire in the previous session and attitude valence reported in the pre-task questionnaire in the current session. *When this variable was measured:* Derived from attitude valence, so this variable is defined and available for all sessions after the first. *Data from which session to be used in data analysis:* As of beginning of session 3.
Attitude Confidence (Berger and Mitchell 1989)
Definition: How certain a person is in his/her attitude. *Nature of measures:* Perceptual, to be captured in questionnaires. *Measures:* * Conf1: How confident are you in the estimation of the goodness of personalized items? (1 = very unconfident; 9 = very confident) Conf2: How precise is your estimation of the goodness of personalized items? (1 = very imprecise; 9 = very precise) *When this variable was measured:* We captured this variable in all pre-task (except session 1) and post-task questionnaires. *Data from which session to be used in data analysis:* Data from the post-task questionnaire in session 3.
Depth of Processing (Petty and Cacioppo 1986)
Definition: The extent to which the person carefully thinks about each recommendation provided by the personalization agent. *Nature of measures:* Behavioral, to be captured in the course of website navigation. *Measures:* Depth of processing was operationalized as the average number of textual comments that a user wrote to describe their thoughts related to a sampled personalized recommendation. We averaged the total number of textual comments on personalized recommendations by the number of sampled personalized recommendations. *When this variable was measured:* As a moderator of link between quality of personalization and perceived usefulness, measured at session 3; as an antecedent of attitude persistence, measured at session 2. *Remarks*: We captured this variable in the lab study, but not in the field study.
Subsequent Breadth of Sampling (Tam and Ho 2005)
Definition: The number of personalized recommendations that a user samples in a particular session. *Nature of measures:* Behavioral, to be captured in the course of website navigation. *Measures:* Subsequent breadth of sampling was operationalized as the number of sampled personalized recommendations in the logon session after we captured attitude confidence. *When this variable was measured:* In all sessions. *Data from which session to be used in data analysis:* Session 4.
Cumulative Breadth of Sampling
Definition: The total number of personalized recommendations that a user had sampled up to and including a particular session. *Nature of measures:* Behavioral, to be captured in the course of website navigation. *Measures:* Cumulative breadth of sampling was operationalized as the total number of sampled personalized recommendations in *all* logon sessions before we captured attitude confidence. *When this variable was measured:* We captured breadth of sampling from the personalization agent in all logon sessions. Thus, theoretically, we were able to calculate *cumulative* breadth of personalized sampling for any round of visits. *Data from which session to be used in data analysis:* Total of breadth of sampling from the personalization agent from sessions 1 to 3.

Actual Selection from the Agent (Tam and Ho 2005, 2006)

Definition: Whether a person chooses a personalized recommendation as his/her final selection.
Nature of measures: Behavioral, to be captured in the course of website navigation
Measures: It was a binary number. “1” refers to a choice of a personalized item as a participant’s item selection, and “0” refers to otherwise.
When this variable was measured: In all sessions.
Data from which session to be used in data analysis: Session 3.

Perceived Usefulness (Van der Heijden 2004)

Definition: The degree to which a person believes that using the personalization agent would enhance his/her performance in product selection.
Nature of measures: Perceptual, to be captured in questionnaires.
Measures:

Study 1: The lab study
By using the personalization agent,
PU1: I could decide more quickly which book I wanted to select than in the past.
PU2: I could better decide which book I wanted to select than in the past.
PU3: I was better informed about relevant books.
PU4: I could decide more quickly whether I wanted to explore a particular book or not.
PU5: I could better decide whether I wanted to select a particular book or not.

Study 2: The field study
By using the personalization agent,
PU1: I could decide more quickly which song I wanted to select than in the past.
PU2: I could better decide which song I wanted to select than in the past.
PU3: I was better informed about new songs.
PU4: I could decide more quickly whether I wanted to explore a particular song or not.
PU5: I could better decide whether I wanted to select a particular song or not.

When this variable was measured: In all post-task questionnaires.
Data from which session to be used in data analysis: Data from the post-task questionnaire in session 3.

Attitude Valence (Bhattacherjee and Premkumar 2004)

Definition: The direction and extremity of an attitude.
Nature of measures: Perceptual, to be captured in questionnaires.
Measures: *

Study 1: The lab study
Valence1. Using the personalization agent in my book selection is a (bad … good) idea.
Valence2. Using the personalization agent in my book selection will be (unpleasant … pleasant).
Valence3. Overall, I (dislike … like) the idea of using the personalization agent in my book selection.

Study 2: The field study
Valence1. Using the personalization agent in my song selection is a (bad … good) idea.
Valence2. Using the personalization agent in my song selection will be (unpleasant … pleasant).
Valence3. Overall, I (dislike … like) the idea of using the personalization agent in my song selection.

When this variable was measured: We captured this variable in all pre-task (except session 1) and post-task questionnaires.
Data from which session to be used in data analysis: Data from the post-task questionnaire in session 3.

Need for Cognition (Cacioppo and Petty 1982)—a control variable
Definition: A personality variable reflecting the extent to which people engage in and enjoy effortful cognitive activities. *Nature of measures:* A self-reported personality trait, to be captured in a pre-task questionnaire. *Measures:* NFC1. I would prefer complex to simple problems. NFC2. I would prefer a task that is intellectual, difficult, and important to one that is somewhat important but does not require much thought. NFC3. I find little satisfaction in deliberating hard and for long hours. (reversely-coded) NFC4. I prefer to think about small, daily projects to long-term ones. (reversely-coded) NFC5. I think primarily because I have to. (reversely-coded) NFC6. I tend to set goals that can be accomplished only by expending considerable mental effort. *When this variable was measured*: Session 1.
Motivation (Deci et al. 2001)—a control variable
Definition: How eager a person is to form a correct judgment. *Nature of measures:* Perceptual, to be captured in post-task questionnaires. *Measures:* Mot1: The book-selection task was important. Mot2: I attached great importance to the book-selection task. *When this variable was measured:* We captured this variable in all post-task questionnaires. *Data from which session to be used in data analysis:* Data from session 3. *Remarks*: We captured this variable in the lab study, but not in the field study.
Ability (Tam and Ho 2005)—a control variable
Definition: How capable a person is to form a correct judgment. *Nature of measures:* Perceptual, to be captured in post-task questionnaires. *Measures:* Ability1: I was capable of selecting a book to fulfill the book-selection task. Ability2: I was knowledgeable about the book topic specified in the book-selection task. *When this variable was measured:* We captured this variable in all post-task questionnaires. *Data from which session to be used in data analysis:* Data from session 3. *Remarks*: We captured this variable in the lab study, but not in the field study.

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Appendix C

Construct Validation for the Lab Study

Table C1. Factor Analysis (The Lab Study) (Note: loadings below 0.30 excluded)

	NFC	PU	Valence	Persist	Quality	Mot	Ability	Conf
Mot1						0.960		
Mot2						0.966		
Ability1							0.857	
Ability2							0.882	
NFC1	0.852							
NFC2	0.794							
NFC3	0.842							
NFC4	0.846							
NFC5	0.840							
NFC6	0.812							
Quality1		0.459			0.774			
Quality2		0.445			0.786			
Quality3					0.876			
PU1		0.831						
PU2		0.852						
PU3		0.826	0.337					
PU4		0.797			0.395			
PU5		0.874						
Valence1		0.336	0.891					
Valence2		0.341	0.905					
Valence3		0.390	0.871					
Persist1				0.863				
Persist2				0.909				
Persist3				0.898				
Conf1				0.414				0.742
Conf2								0.903

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
Note: Mot = Motivation; Ability = Ability; Quality = Quality of Personalization; PU = Perceived Usefulness; Valence = Attitude Valence; Conf = Attitude Confidence; Persist = Attitude Persistence, NFC = Need for Cognition.

Table C2. Reliability, Correlations and AVE (The Lab Study)

	Reliability	1	2	3	4	5	6	7	8
1. Motivation	0.926	**0.982**							
2. Ability	0.731	0.288	**0.883**						
3. Need for Cognition	0.917	-0.051	-0.137	**0.839**					
4. Quality of Personalization	0.911	-0.067	0.076	-0.100	**0.921**				
5. Perceived Usefulness	0.943	0.075	0.116	-0.163	0.658	**0.904**			
6. Attitude Valence	0.957	0.065	0.089	-0.153	0.398	0.607	**0.977**		
7. Attitude Confidence	0.779	0.204	0.099	-0.117	0.122	0.223	0.265	**0.904**	
8. Attitude Persistence	0.893	0.156	0.059	-0.044	0.065	0.114	0.153	0.505	**0.907**

Note: Diagonal entries (bold) are the square root of the average variance extracted (AVE).

Appendix D

The Path Analysis of Study 1—The Lab Study—Using Sessions 1–3 Data

Figure D1 depicts the path analysis model for the lab study using sessions 1-3 data. We followed the report of modification indices to include two additional paths: NFC ↔ motivation and attitude valence → subsequent breadth of sampling. The model showed a CFI of 0.948 and a TLI of 0.948, a WRMR of 1.01, and a RMSEA of 0.080. The CFI (close to the cutoff of 0.95), TLI (close to the cutoff of 0.95), and RMSEA (< cutoff of 0.08) were satisfactory, but WRMR was larger than the cutoff of 0.9. This model demonstrated a reasonably good fit. The R-squares of the dependent variables were satisfactory—0.201 for depth of processing; 0.523 for perceived usefulness; 0.862 for subsequent breadth of sampling; 0.603 for attitude confidence; 0.338 for attitude persistence; 0.421 for attitude valence; and 0.812 for item selection.

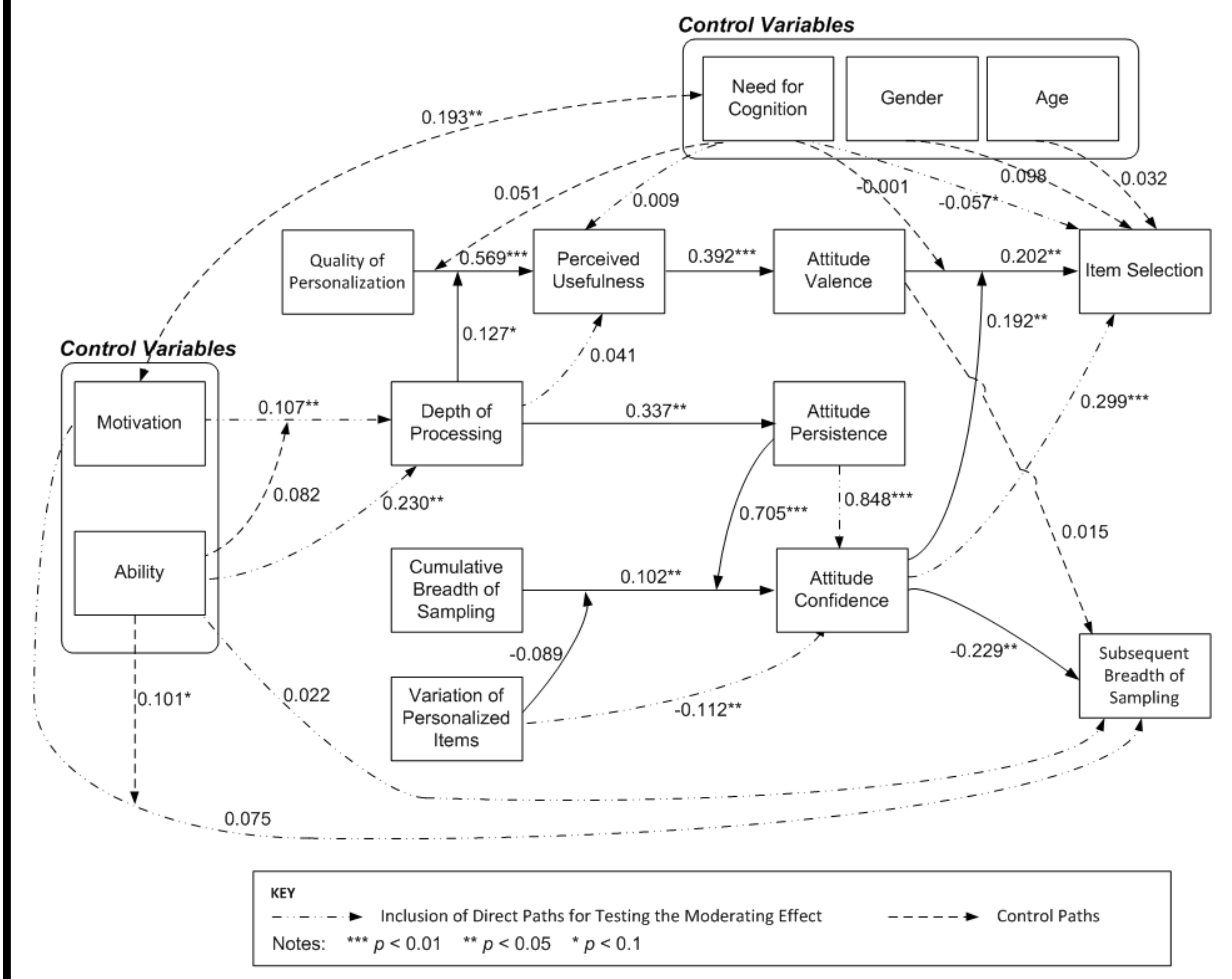

Figure D1. Path Analysis of the Lab Study (Sessions 1–3)

Appendix E

Construct Validation for the Field Study

Table E1. Factor Analysis (The Field Study) (Note: loadings below 0.30 excluded)

	PU	NFC	Valence	Persist	Quality	Conf
NFC1		0.743				
NFC2		0.622				
NFC3		0.748				
NFC4		0.659				
NFC5		0.657				
NFC6		0.675				
Quality1					0.764	
Quality2					0.742	
Quality3					0.754	
PU1	0.799					
PU2	0.820					
PU3	0.754					
PU4	0.773					
PU5	0.692					
Valence1			0.710			
Valence2			0.831			
Valence3			0.824			
Persist1				0.877		
Persist2				0.930		
Persist3				0.935		
Conf1						0.936
Conf2						0.930

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
Note: Quality = Quality of Personalization; PU = Perceived Usefulness; Val = Attitude Valence; Conf = Attitude Confidence; NFC = Need for Cognition.

Table E2. Reliabilities, Correlations and AVE (The Field Study)

	Reliability	1	2	3	4	5	6
1. Need for Cognition	0.780	**0.706**					
2. Quality of Personalization	0.877	0.177	**0.794**				
3. Perceived Usefulness	0.859	0.166	0.393	**0.798**			
4. Attitude Valence	0.742	0.097	0.278	0.079	**0.799**		
5. Attitude Confidence	0.799	0.146	0.017	0.051	0.069	**0.942**	
6. Attitude Persistence	0.863	-0.059	0.051	-0.007	-0.127	0.002	**0.946**

Note: Diagonal entries (bold) are the square root of the average variance extracted (AVE).

Appendix F

The Path Analysis of Study 2—The Field Study—Using Sessions 1–3 Data

Figure F1 depicts the path analysis model for the field study using sessions 1–3 data. The model showed a CFI of 0.953 and a TLI of 0.950, a WRMR of 0.72, and a RMSEA of 0.040. The CFI (> cutoff of 0.95), TLI (> cutoff of 0.95), WRMR (< cutoff of 0.9), and RMSEA (< cutoff of 0.08), were satisfactory, and this demonstrated a good model fit. The R-squares of the dependent variables were satisfactory—0.203 for perceived usefulness; 0.319 for subsequent breadth of sampling; 0.435 for attitude confidence; 0.101 for attitude valence; and 0.129 for item selection.

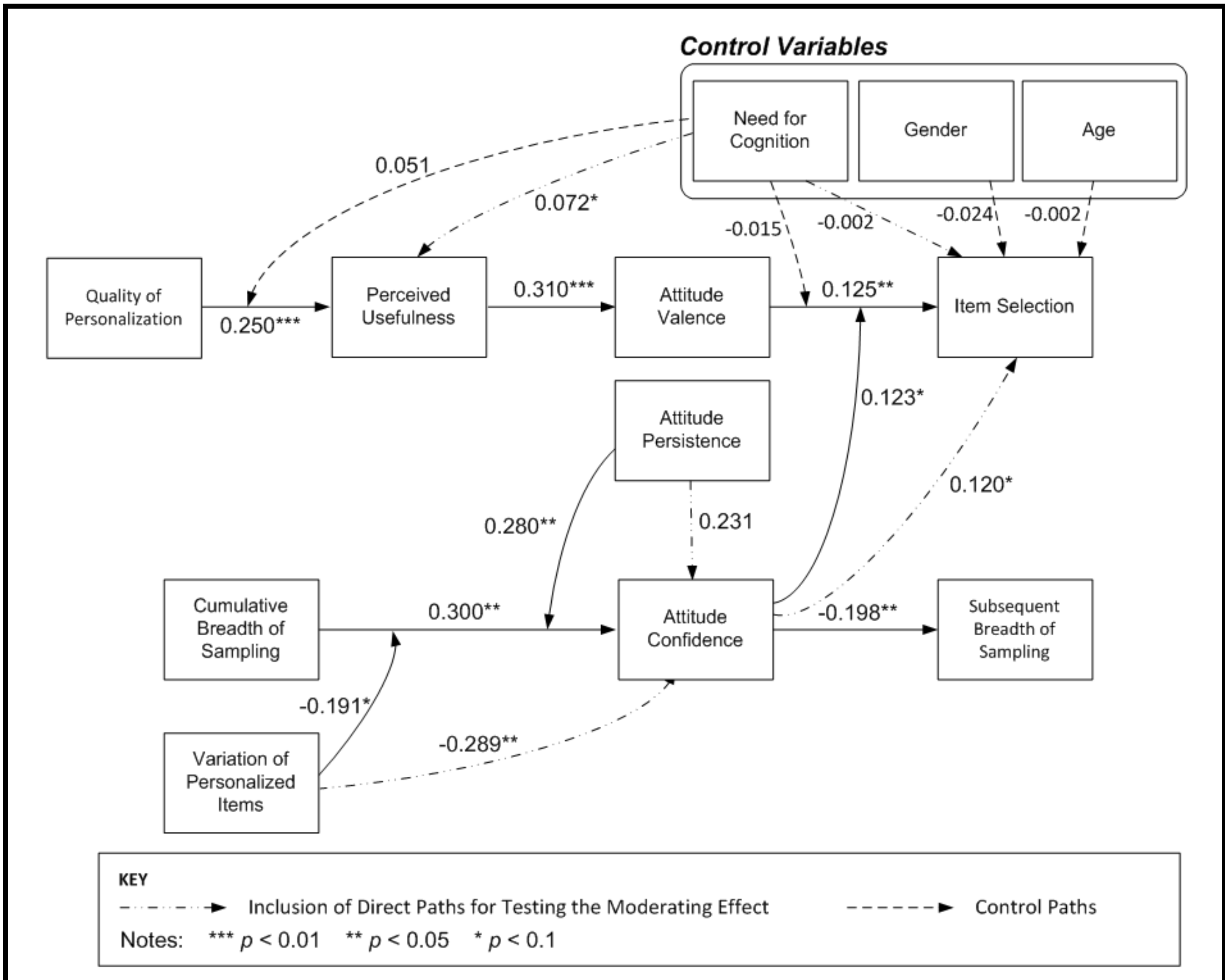

Figure F1. Path Analysis of the Field Study (Sessions 1–3)