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Content Learning on Websites

The Effects of Information Personalization

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CONTENT LEARNING ON WEBSITES: THE EFFECTS OF INFORMATION PERSONALIZATION

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ABSTRACT

Information personalization is a popular and effective way used especially by online content providers to reduce user effort for the assessment of abundant information load. Based on learning and goal setting theories, in this paper we argue that the successful role of information personalization can be attributed to the effect of increased content learning, which is a key driver of consumer website evaluation and loyalty. In addition, we distinguish between two dimensions of information personalization and suggest that effort reduction due to information personalization is not necessarily beneficial. Based on two experimental studies using a health information website, we demonstrate that personalization content, which decreases the effort through offering dense information tailored to the users' needs, leads to beneficial behavioral outcomes (website evaluation and revisit intention) due to the mediating role of increased content learning. Personalization interaction, which decreases the effort through the process by which the personalized content is generated, has the opposite effects due to the decreased ability of information retention.

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1. INTRODUCTION

Online consumers can access large amounts of content from a wide range of information sources. However, although consumers in these information rich environments often have ample access to information, most of that information typically is not relevant to their purpose (Duan et al. 2009). Therefore, even online consumers—because they have limited time to search—tend to naturally stick with content providers with whom they have interacted successfully in the past even if this behavior diverts from their optimal choice (Johnson et al. 2003). In order to overcome this inertia that may lead to suboptimal consumer information use even when large amounts of information are available, companies have introduced online decision aids and personalized information services to help consumers sort through the information overload. Such personalization processes represent a very popular strategy in online content management and are widely researched in the fields of information systems (IS) (Awad & Krishnan 2006; Chelappa and Sin 2005; Komiak and Benbasat 2006; Tam and Ho 2006) and marketing (Ansari and Mela 2003; Suprenant and Solomon 1987). Information personalization is an effective way to reduce customer search costs and improve the efficiency of a website, leading into increased visits and superior performance in terms of decision quality (Ansari and Mela 2003; Tam and Ho 2005). However, there is a risk that too much personalization may backfire for example if consumers prefer to have a choice over the information they access (Lee and Lee 2009). While the majority of online companies commonly use elements of personalized content in their interactions with their customers, there is considerable debate regarding whether personalization increases visitor evaluations and repeat visits—especially regarding content-based websites (i.e.

news, entertainment) (Aberdeen Group 2007; Jupiter Research 2003; Liu et al. 2010). Although information personalization can reduce content overload, it may lead to situations where users are less satisfied with the content they end up with (Parisier 2011). This concern is related to a previous study that showed that only 30% of online consumers found personalized content valuable (Mulpuru et al. 2007). Therefore a better understanding of information personalization may help firms that need to evaluate the benefits of making investments in their websites to increase personalization in order to justify the cost associated with offering the personalization (Liu et al 2010).

We distinguish between two dimensions of information personalization that jointly determine the likely success of the personalization process. (1) *Personalization Content* refers to the information provided to the customer and more specifically the degree to which it is uniquely tailored to the individual (Chellappa and Sin 2005; Liang et al. 2007). The amount of personalized information can vary and therefore higher personalization content is related to more focused and relevant information content that decreases the information load of the users (Jacoby et al. 1974). (2) *Personalization Interaction* refers to the process by which the personalized content is generated. It captures the degree to which the user interactively engages in the online information search environment to obtain personalized information (Bates 1990). Based on this approach, the user can actively perform the personalization himself or passively receive and consume personalized information (Wallin 1999). Increasing or decreasing in either dimension has the potential to substantially affect the quality of the outcome of consumers' information search as well as the required consumer effort in search (e.g., time spent or cognitive elaboration) (Haubl and Trifts 2000; Todd and Benbasat 1994). Greater search effectiveness and lower effort are likely to lead to a higher level of customer satisfaction towards using the website and a higher retention rate.

Prior research on information personalization has emphasized its beneficial effects on the quality of the decisions of the users (Haubl and Trifts 2000; Tam and Ho 2006) as well as the drivers of consumers' adoption and evaluation of personalization technologies (Komiak and Benbasat 2006). However, an aspect which has received relatively little attention—and which is particularly relevant for information personalization—is how personalization affects the amount of consumer *content learning* that takes place. Content learning is the bridge between behavioral response and environmental stimuli. In cognitive science, learning is seen to have a central role in the interaction between users and websites (Vandenbosch and Higgins 1996). This is especially applicable for content-based websites, such as news and health information delivery websites, where the information offered is the main value component of the website (Huizingh 2000; Liu et al 2010). A key objective of online information search for consumers on such websites is to learn more about a certain topic and therefore the quality of the website merely depends on the content that is accessed (Castaneda et al. 2007; Mithas et al. 2006-7). As a result it is highly relevant to examine how online knowledge formation can best be supported by various information retrieval modes applied by websites.

In this paper, we argue that personalization can help improve consumer content learning on content-based websites and that content learning subsequently forms a key driver of consumer website evaluation and loyalty. Based on learning and educational theories we expect that personalized materials have a greater effectiveness compared to traditional learning techniques (McLeod 2003; Bonwell and Eison 1991). In an online information context, the perceived usefulness and effectiveness of a website is related to the extent to which the website can help consumers retrieve and understand the required information (Jiang & Benbasat 2007b, Todd and

Benbasat 1987). In addition, based on goal setting theories, goal achievement such as increased content learning leads to higher degrees of satisfaction and attitude towards the medium (Locke and Latham 1990). Consequently, we expect that increased content learning plays an important role in the formation of a positive attitude towards content-based websites as well as on the continuance intention on the website. Repeated visits are essential for content-based websites since they increase the popularity of the website and thus increase advertising offers, which is the main source of profitability for this type of websites.

This leads us to the main research questions for this study. First, what is the role of content learning to explain the beneficial effect of information personalization on the evaluation and continuance intention of a website? Second, how do the two proposed dimensions of personalization (personalization content and personalization interaction) work together to influence website evaluation and revisit intention of consumers and to what extent can these effects be attributed to content learning? To study these research questions, we conducted two laboratory experiments using a health information website. In the first study, we investigated the beneficial role of content learning with respect to increasing evaluations and revisit intentions of a website. We also demonstrate the general effectiveness of information personalization compared to a generic information setting. We found that differences in website evaluations and repeat visit intentions can be attributed to the effect of increased content learning in the case of personalized information. In the second study, we introduced two information personalization dimensions. We first confirmed the crucial role of content learning towards continuance intention and evaluation of the website. Also, we examined how different ways of personalizing information in a given website have different effects on content learning, website revisit intention and evaluation of the website. We showed that effort reduction due to information personalization is not necessarily beneficial. More specifically, on one hand, we found that decreasing users' effort due to greater personalization of the content is beneficial in terms of website evaluation and continuance intention (fully mediated by the increased content learning). On the other hand, we found that decreasing consumers' effort in the personalization interaction is not beneficial and leads to lower behavioral outcomes (due to decreased content learning).

The current study contributes to IS literature in several ways. Prior research in IS has examined the relationship between personalization and system evaluation (Komiak and Benbasat 2006; Tam and Ho 2006). However, this is the first paper to examine the role of content learning in explaining the effectiveness of information personalization. In addition, we propose a decomposition of information personalization into two distinct dimensions, namely personalization content and personalization interaction. These dimensions are related to the amount of effort needed by the users in relation to the outcome and the process of information personalization respectively. Based on the proposed distinction, we show that greater personalization is not always beneficial proposing that the foundation for this effect is linked to the concepts of user effort and content learning. Finally, we expand the literature related to the important area of content-based websites (Huizingh 2000; Liu et al. 2010; Mithas et al. 2006-7).

The remainder of this paper is organized as follows. First, we review relevant theories regarding personalization and learning. We then develop a set of hypotheses pertaining to how we expect information personalization levels to affect content learning outcomes, evaluation of the website and intention to revisit the website. This is followed by a description of the methodology used to test the hypotheses and the results of our empirical studies. The paper concludes with a general discussion of the findings, theoretical and managerial implications, as well as limitations and future research.

2. THEORETICAL BACKGROUND

2.1 Information Personalization

Information personalization in a general sense refers to the process of providing customers with customized content and services by using their personal and preference information gathered from their interaction with the provider according to their needs and tastes (Chellappa and Sin 2005; Liang et al. 2007). Some of the most popular definitions of personalization refer to customizing some features of a service, to individualized communication based on stated or implied preferences, or to changes in a service to better match customer needs (Vesanen 2007).

In the academic IS literature, various studies dealt with ways to acquire information about consumer needs and convert this information to provide personalized recommendations (Adomavicius and Tuzhilin 2003; Mobasher et al. 2000). Another stream of research aims at identifying the conditions under which personalization is effective. Tam and Ho (2006) developed a model that posits that personalization effectiveness is moderated by content relevance and self reference. Komiak and Benbasat (2006) proposed that the adoption of a recommendation agent is influenced by the perceived personalization and the level of familiarity of the users. Additionally, Tam and Ho (2005) considered the application of the elaboration likelihood model from the consumer behavior literature and found that a consumer's need for cognition may play a role in the effectiveness of web personalization. Further, prior studies also looked at when to personalize as well as how much (Ho et al. forthcoming; Liu et al. 2010). In the marketing literature, studies on personalization are mainly related to personal interactions as an integral part of the service process (Suprenant and Solomon 1987). Personalized product recommendation can enable customers to identify superior products with reducing their search effort, which can lead to increased performance of the online providers (Ansari and Mela 2003;

Haubl and Trifts 2000).

In this paper we focus on information personalization in a content-based online environment. The effectiveness of a website design in terms of supporting online information search is very important to consumers. For example the completion of online searches is highly influenced by the manner in which information is encoded online as well as the context in which information is retrieved (Jiang and Benbasat 2007b; Locke and Latham 1990). Given the high volume of information that can be found online, companies have attempted to detect what are the most effective ways of providing relevant information in order to satisfy the consumers' needs. Personalized decision aids designed to assist consumers in an online information search have been found to have substantial positive effects on both the quality of the decisions as well as the required effort in search (time spent and cognitive elaboration) (Haubl and Trifts 2000; Todd and Benbasat 1994) which can lead to a higher level of satisfaction with the website. However, there are also cases where personalization is not so effective since it can be perceived as providing incomplete information due to only presenting personalized content (Lee and Lee 2009).

2.2 Dimensions of Information Personalization

Most studies on information personalization have treated information personalization as a one dimensional construct (Chellappa and Sin 2005, Komiak and Benbasat 2006, Liang et al. 2007). Typically the aim of information personalization has been to assist consumers in finding the most relevant information based on their own personal needs. Previous research has proposed ways to refine the concept of personalization. Some studies discussed the distinction between the subject (who does the personalization) and the object (what is personalized) of personalization (Fan and Poole 2006; Wallin 1999). Other researchers in personalization have emphasized the distinction between the outcome and the process of obtaining a personalized result (Suprenant and Solomon 1987). Based on this latter approach, we distinguish between two dimensions in information personalization: personalization content and personalization interaction. Across both these dimensions, information personalization can reduce the effort endured by users and they may do so in different ways. Respectively, the dimensions of personalization content and interaction can be operationalized based on high or low user effort required as follows. *Personalization Content* refers to the degree to which customers are provided with uniquely tailored information on the basis of their own individual needs as gathered from the consumer's interaction with the provider (Chellappa and Sin 2005; Liang et al. 2007). Personalizing content decreases the cognitive effort needed in order to assess the information. *Personalization Interaction* refers to the process by which the personalized content is generated. This second dimension captures the degree to which the consumer interactively engages with the online information search environment to obtain his or her own personalized content (Bates 1990). When a higher degree of interaction is needed from the user, this may increase the effort required for accessing the information. We explain and illustrate these two dimensions in Figure 1.

Personalization Content. Personalization content is related to the outcome of the personalization offered by a website. Due to the vast amount of information available on the web, locating the most relevant information is often a difficult task for consumers. As a result, the information overload may hinder the effectiveness of the search (Malhotra 1982). Information personalization is expected to assist consumers to overcome this problem by providing information more focused around the most related and necessary information. The degree of personalization content can vary depending on the final outcome. We speak of *focused personalization content*, when the search results provide concentrated and relevant information content and require lower effort from users. Based on the requested personal information, the focused information is filtered out from any information besides the core and most necessary for the specific personal query of the consumer. In this way, the effort needed by a consumer to search for relevant information is reduced (Jacoby et al. 1974; Liang et al. 2007). On the other hand, *extensive personalization content* exists when the consumer accesses a greater amount of information, which—although still personalized—requires higher effort from searchers to identify the most relevant information compared to more focused content.

Personalization Interaction. Another important aspect of information personalization is how users interact with the system in order to access the information outcome. This dimension captures the degree to which users have to actively engage with the process of information search. Personalization interaction focuses on who performs the information personalization. The degree of interaction is based on the degree of effort of the user in the process (passive versus active) as well as the control of information flow in the personalization process (system driven versus user driven). One of the main characteristics of personalization is that it affects the user effort needed for the search (Haubl and Trifts 2000). Based on this assumption, we distinguish two levels of personalization interaction based on low versus high effort needed for personalization by a user. A user can be either passive or may need to be active in the process of personalization. When the user is active, the interaction required is higher and therefore, the effort needed by the users is also higher compared to a more passive user who just consumes information (Wallin 1999).

Passive personalization interaction exists when a website offers tailored information based on individual queries without much involvement of the users. In this case, the website takes all control in finding and providing the appropriate information to customers (Khalifa 2002; Bates 1990). The consumer effort involved in passive personalization is relatively low. *Active* *personalization interaction* exists when the user has more responsibility in finding the required information. In this case, the website offers some answers based on individual queries but leaves the users to control the information flow and evaluate and choose the most appropriate information (Ariely 2000). Thus the consumer effort involved is considered relatively high.

Figure 1. Information Personalization: A User Effort Based Classification

<table>
<tr><td colspan="2"></td><td colspan="2">Personalization Content</td></tr>
<tr><td colspan="2"></td><td>Extensive</td><td>Focused</td></tr>
<tr><td rowspan="2">Personalization Interaction</td><td>Active</td><td>High Interaction Effort / High Content Effort</td><td>High Interaction Effort / Low Content Effort</td></tr>
<tr><td>Passive</td><td>Low Interaction Effort / High Content Effort</td><td>Low Interaction Effort / Low Content Effort</td></tr>
</table>

2.3 The Role of Content Learning

The role of content learning has been highlighted in many aspects of human behavior. Cognitive psychologists introduced the notion that learning is based on the mental changes in behavior due to the interaction between cognitive processing in the mind and environmental stimuli (Neisser 1967). In order to holistically capture the nature of human learning, psychologists proposed different mental models that influence the effectiveness of learning outcomes (i.e. behaviorist, cognitivist and constructivist approach) (Bargh and Ferguson 2000; Kettanurak et al. 2001). Therefore, cognitive absorption of certain content depends not only on the amount and nature of the content an individual receives (i.e. cognitive load theory) but also on the learning approach the individual uses such as learning by doing (goal directed problem solving) versus learning by knowing, or active versus passive learning (Bostrom et al. 1990; Shuell 1986). The process of learning is stimulated by the information that is encountered and perceived. In particular, the cognitive absorption of individuals directly influences their response to the environmental stimuli and therefore user behavior is a result of the learning performance of the users (Shuell 1986; Vandenbosch and Higgins 1996; Wittrock 1974). Thus, the role of content learning operates as a substantive bridge between the information that is accessed and the individual's further behavior.

In an educational environment, the cognitive performance can be a strong indicator of the effectiveness of the educational institution. Research has found that a way to increase cognitive performance of students is to personalize the learning process, because it can lead to an increase in student motivation and engagement (Cordova and Lepper 1996). The effectiveness of personalization in education is related to the degree to which the process as well as the content of the learning experience matches the users' cognitive styles and needs. There is also evidence to show that increasing learners' control over the learning process increases the effectiveness in terms of learning outcomes, leading to better student attitudes and improvements in students' cognitive development (Bonwell and Eison 1991; Khalifa and Lam 2002; Laws et al. 1999). Shifting to an online learning environment, the performance of learners in terms of task achievement and memory-based recall has been used as a strong indicator of e-learning programs effectiveness (Arbaugh and Benbunan-Fich 2007; Chiu and Wang 2008; Piccoli et al. 2001; Wan et al. 2008).

Similar to an educational context, searching for information on content-based websites is also a goal-directed behavior focused on information acquisition and comprehension (Liu et al. 2010; Mithas et al. 2006-7). The effectiveness of information search is crucial for consumers since a successful search leads to the achievement of their goal and in turn to higher satisfaction levels (Locke and Latham 1990). In such a context, learning refers to any process that changes users' memories and behavior as a result of improved information processing (Vandenbosch and Higgins 1996). Recent research in IS showed that different types of presentation formats have a substantial effect on the amount of product learning (Jiang and Benbasat 2007a; Jiang and Benbasat 2007b; Nicholson et al. 2008; Parboteeah et al. 2009; Suh and Lee 2005). To date, there is limited empirical research about what users learn from their use of websites or what the effects of learning are (Eveland et al. 2004). Mostly, previous studies have focused on the process and the acquisition of user skills (i.e. website knowledge) rather than the content learning (i.e. product knowledge) (Murray and Haubl 2002; Zhang et al. forthcoming). Thus, while process oriented learning relates to the efficacy of use for a given website, content learning relates to the declarative level of knowledge formation that the user succeeds and is equally important as process learning (Mittal and Sawhney 2001; Smith 1990). Content learning is related to the users' cognitive performance and drives their attitude towards a system (Dabholkar and Bagozzi 2002). In this study, we examine the effect of content learning in relation to information personalization in the context of content-based websites.

3. CONCEPTUAL MODEL AND HYPOTHESES DEVELOPMENT

In this section we discuss the proposed relationships in our conceptual model and develop the hypotheses. The first set of hypotheses introduces the beneficial role of content learning regarding website evaluation and revisit intention. In the second set of hypotheses, the role of content learning in explaining the positive effects of information personalization on website evaluation and website revisit intentions is investigated. In the last set of hypotheses, we disentangle the two dimensions of information personalization in order to better understand the effects of reducing user effort on behavioral outcomes towards the website.

3.1. The Effects of Content Learning

The concept of learning has been used in IS research to develop an indication of the effectiveness of information transmission by different system interfaces (Large et al. 1994).

When visiting a content delivery website, a user wishes to learn something new (learning goal) or to find information that can facilitate her decision making (decision making goal). In both cases, the main goal is to access the most relevant information. Therefore, the learning outcome of the information search can reflect the achievement of the user's goal and can be a driver of the evaluation of the experience (Browne and Pitts 2007). After each visit, users form implicitly an assessment of the website's performance. Many studies in IS have dealt with investigating the importance of information and system quality and how they influence users' behavioral and attitudinal outcomes (DeLone & McLean 2003; Nelson et al 2005; Palmer 2002). These construct are closely related to users' satisfaction (Abdinnour-Helm et al. 2005). The amount of content learning signifies the degree of effectiveness and perceived usefulness of a website. Content learning is related to the users' performance during a website visit and therefore can affect their attitude towards it (Dabholkar and Bagozzi 2002). In education, the cognitive performance of students (measured in grades) is a major antecedent of their satisfaction from their academic experience (Umbach 2000). Similarly, the degree to which a website can offer understandable and relevant information can positively affect users' attitudes towards it (Jiang and Benbasat 2007a). Therefore, we propose:

- **Hypothesis 1a.** *Greater content learning increases website evaluation.*

An essential driver of long term success of a website is the formation of a returning user base. System continuance intention (or website loyalty) has received an extensive amount of attention in the literature (Bhattercherjee 2001; Limayem et al. 2007). Learning experiences from a website can become a key source of competitive advantage for online firms because they can lead to higher consumer retention (Mittal and Sawhney 2001). In online learning systems, content learning explains post-learning behaviors, such as word of mouth and reuse intention

(Wang 2003). In content-based websites, the fulfillment of users' needs positively influences their intention to remain loyal to the website (Gummerus et al. 2004). In addition, research in higher education has highlighted the importance of knowledge formation in the effectiveness of applied learning techniques (Umbach 2000). Learning influences student commitment and retention to the current educational institution (Aitken 1982; Hartman and Schmidt 1995). Since in such cases the main need is to access the right information from the website, we expect that higher content learning from a website will lead to a higher intention to revisit the website. Therefore we expect that:

- **Hypothesis 1b.** *Greater content learning increases the intention to revisit the website.*

3.2 Information Personalization and Content Learning

Personalized information has been proven to be effective in terms of knowledge retention in health and education studies (Khalifa and Lam 2002). Offering personalized content on a topic increases the chances of that information to be read and assimilated by users compared to generic information (Strecher et al. 2005). In an educational environment, cognitive performance of students is increased with the personalization of the learning process (Arbaugh and Benbunan-Fich 2007; Cordova and Lepper 1996). Evidence has shown that personalization can lead to improvements in students' cognitive development, allowing them to tailor their experiences to meet their personal learning objectives (Bonwell and Eison 1991; Laws et al. 1999). Since information personalization typically increases the relevance of the content accessed by users, this content is more likely to be remembered and appreciated than non-personalized content (Oenema et al. 2001; Tam and Ho 2006). In such a situation, users can faster and more accurately retrieve information from memory, since the associations in memory become stronger (Tam and Ho 2006). Also, users who access personalized information are expected to show increased involvement in the elaboration of the information than those who receive less relevant information. In addition, since information personalization reduces the cognitive effort of the users, given their finite cognitive capacity, users can assess the information in a more elaborate way. Therefore we hypothesize that:

- **Hypothesis 2a.** *Offering personalized information on a website increases content learning.*

The outcome of a search task influences the evaluation of the search experience of users (Browne and Pitts 2007). In retrospect, all behavioral responses are affected by the stimuli that the visitor faces when searching for information. In addition, learning is known to be a link between environmental stimuli and subsequent behaviors of the users (Shuell 1986; Vandenbosch and Higgins 1996; Wittrock 1974). Users perceive personalized information as more useful and relevant, and as a result they become more satisfied from the website (Kwon et al. 2010; Tam and Ho 2006). Information personalization reduces the effort required from the users which is beneficial to their website usage experience. As a result the quality of their decisions is also likely to increase, leading to increased satisfaction and evaluation of their website experience (Haubl and Trifts 2000, Liang et al. 2002, Todd and Benbasat 1994).

Personalized information offers higher content relevance to the users, and therefore the content is expected to be better assimilated by them compared to non-personalized content (Oenema et al. 2001; Tam and Ho 2006). The higher expected amount of content learning derived from personalized information indicates a higher degree of efficiency of a website. Also it was shown that higher cognitive outcomes of a system's user can positively affect his attitude towards it (Jiang and Benbasat 2007a; Umbach 2000).

Finally, we expect that when controlling for the amount of content learning, the beneficial effect of information personalization on website evaluation diminishes. The reason is that the positive effect of information personalization on website evaluation can be attributed to a large degree to the extent of content learning in the website. Information personalization is expected to increase content learning, which in turn increases the evaluation of the website. The amount of learning can be used as a mediator of potential behavior (Suh and Lee 2005; Smith 1990). Content learning is closely related with the goal achievement of the users of a content-based website, accomplishing this goal increases their satisfaction and as a result their website evaluation. Also, Mittal and Sawhney (2001) suggested that content oriented learning from a website can lead to more positive feedbacks of the website. If content learning is low, users may feel frustrated or disappointed because they do not feel confident about the level of achievement and therefore the positive effects of information personalization will substantially decrease. Reversely, when users learn more, their website self-efficacy increases. This effect can lead to more favorable evaluation of the source of information (Bandura 1997). Therefore, we hypothesize that:

- **Hypothesis 2b.** *The positive effect of information personalization on website evaluation is mediated by content learning.*

Research suggests that information personalization can build up continuance intention of a system (Mark & Vogel 2009). In the case of digital products (i.e. content of informational websites such as news), offering personalized content to the users showed increased effectiveness as well as higher preference for further use (Kreuter et al. 2000). Similarly, a higher preference for website continuance was found when users had received personalized information in an earlier visit (Oenema et al. 2001). The reason is that when a website offers personalized information to its users, it better satisfies their needs than by following one-size-fits-all approaches. This also increases the perceived usefulness due to relevance of the offered information (Castaneda et al. 2007; Tam & Ho 2006). As a result, personalization can lead to higher continuance intention by enhancing consumer satisfaction and trust towards the website, which both are the strongest antecedents of loyalty (Gummerus et al. 2004). In addition, personalization has the advantage of reducing the time and effort needed from the user in order to complete a task (Haubl and Trifts 2000). Finally, personalized content has been linked to higher process learning leading to increased switching barriers of the website (Murray and Haubl 2007).

Content learning on a website can increase the likelihood of consumer revisit intentions (Mittal & Sawhney 2001; Wang 2003). Since personalized information leads to more accurately recalled information (Tam & Ho 2006), given the positive influence of content learning on intention to revisit a website, we expect that the beneficial effect of personalization mechanisms on revisit intentions is captured by the learning effect. If a user has access on personalized information but fails to adequately assimilate the content of the information, the user might feel that the website is not able to serve its role and therefore divert to another website in the future. Information personalization has also been found to increase intention of word of mouth promotion of compared to providing generic information (Strecher 2005). The reason is that tailored information is more likely to be read and remembered compared to generic information. Therefore, we expect that:

- **Hypothesis 2c.** *The positive effect of information personalization on intention to revisit the website is mediated by content learning.*

3.3. Personalization Content and Content Learning

Information personalization assists consumers to deal with the amount of information that can be found online and may lead to information overload (Malhotra 1982). Therefore, the degree of personalization of the content that takes place on a website influences the expected effort needed from the users. Users have finite processing capacity to absorb information. If they are provided with "too much" information, such that it exceeds their processing limits, information overload occurs, leading to poorer decision making and dysfunctional performance (Malhotra 1982). Cognitive load theory in education posits that facilitation of learning can be achieved by directing cognitive resources toward activities that are relevant to learning rather than mentally integrating large amounts of information (Eveland and Dunwoody 2001; Sweller 1988). By presenting the same information in a more condensed form, consumers' recall is improved. Users have limited working memory to process incoming information and as a result when the amount of information on offer is closer to exceeding their cognitive capacity users may become disorientated and skip important information (Huang 2003; Jiang and Benbasat 2007b). Thus, higher levels of personalization content reduces users' information load and increases content learning. Personalized recommendations are found to be an important feature that facilitates the absorption of the relevant information and lead to higher continuance intention towards the website (Agarwal and Venkatesh 2002).Therefore:

- **Hypothesis 3a.** *More focused personalization of a website's content increases content learning.*

In an online environment, the possibility of information overload is closely related to the increasing volume and diversity of information presented to consumers. Thus, reducing the amount of information presented to users facilitates consumers in understanding the information and avoiding the feeling of confusion that high information loads may infer. Therefore, the perceived usefulness and performance of a content-based website is increased when information can be presented in a more focused manner (Cline and Haynes 2001). Mittal and Sawhney (2001) suggested that content learning in a website can positively influence the evaluation of the visited website. If content learning is low, users may feel that the website does not fulfill its expectations and therefore the effects of focused personalization content on the evaluation of the website are not significant anymore. In particular, we expect that the positive effect of information personalization on website evaluation can (partly) be attributed to the amount of content learning.

Furthermore, personalizing the content reduces users' effort and limits the outcome of the information to only the core part. In that way, users are expected to be more satisfied by the use of the website and as a result that would lead to higher intention to revisit the website (Srinivasan et al. 2002). Users are more satisfied when they can minimize the effort required in a given task. The learning effectiveness of their experience is expected to lead to higher intention to revisit the website (Xiao and Benbasat 2007). We also expect that the positive effect of more focused content personalization on the intention to revisit the website is mediated by the amount of content learning. The reason is that personalizing the content reduces users' effort and narrows the outcome of the information to only the core part. In that way, users are expected to be more satisfied with the use of the website because they are able to assimilate the information they acquire more efficiently. This implies that even at low effort the goal of accessing and learning the desired information, which we expect implies that consumers will want to use the website again in the future. Therefore, we expect:

- **Hypothesis 3b.** *Content learning mediates the positive effect of focused personalization content on website evaluation.*
- **Hypothesis 3c.** *Content learning mediates the positive effect of focused personalization*

content on intention to revisit the website.

3.4. Personalization Interaction and Content Learning

Some information personalization systems require users to be more active to generate their own personalized content whereas other systems take more control and minimize users' required effort. Since effort can be regarded as a cost to the user we consider the former –more active-approach as a lower level of personalization compared to the case where users are more passive in the personalization process. In other words, the more passive the role of the user is, the more personalized the service of the website can be considered. Personalization interaction is also related to the level of control over the personalization process by the user. Here, in contrast to personalization content, we expect that lower effort in the personalization interaction (and hence a higher degree of personalization) decreases the amount of content learning of the users of a content-based website. The literature on education concludes that active learning, where the control of the learning process is given to the student, surpasses traditional lectures in terms of retention of material and general skill development (Bonwell and Eison 1991; Laws et al. 1999). More active strategies of learning can lead to higher learning outcomes and evaluations of the content and structure of the learning process compared to distributed passive learning processes (Khalifa and Lam 2002). Giving control to the learner to draw his own conclusions is beneficial, even if that means the increase of cognitive effort (Sawyer and Howard 1991; Bonwell and Eison 1991). The reason is that information retrieved with high cognitive effort is more likely to be retrieved from memory compared to less effortfully processed information (Tyler et al. 1979). In this line of research, evidence was found regarding increased comprehension of the content of a website influenced by higher levels of involvement, information processing, and learner control as well as the duration of retention of the acquired information (Ariely 2000; Lustria 2007;

Nicholson et al 2008). Based on the "generation effect" when participants self-generate the information, memory performance is better than when the information is explicitly given to them (Kardes 1988; Lichtenstein and Srull 1985). Previous research in IS has showed that more interactive presentation of information are more engaging and can increase the amount of actual knowledge (Suh and Lee 2005). Learning occurs when learners engage in actively processing information presented to them, and when they actively construct mental representations (Jiang and Benbasat 2007b). Therefore:

- **Hypothesis 4a.** *More passive personalization of a website's interaction decreases content learning.*

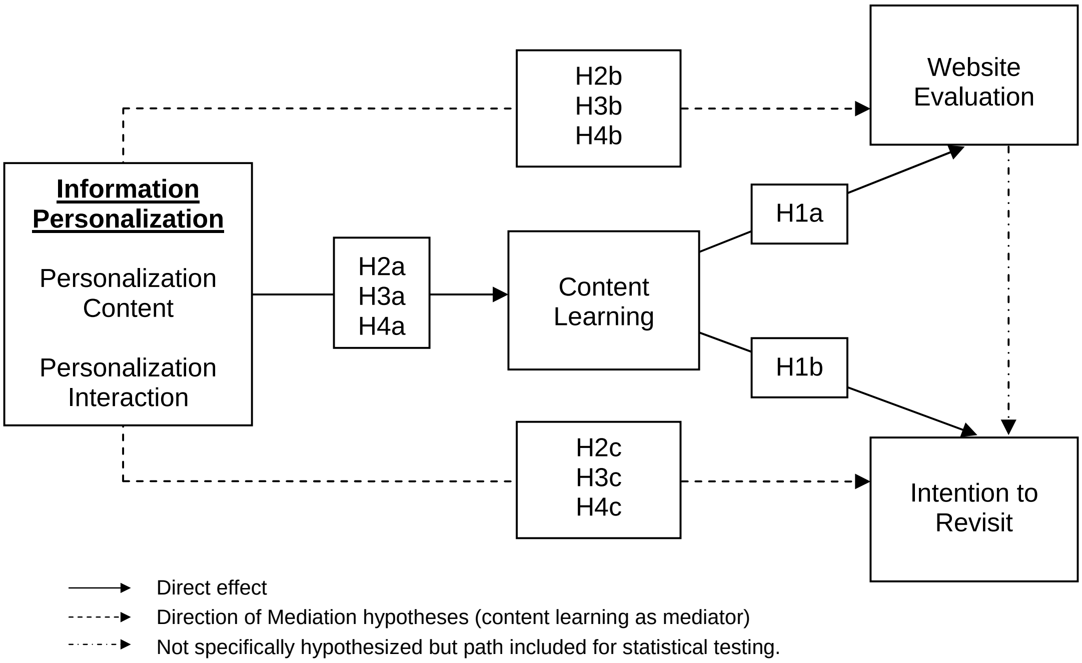
The level of interaction and control users experience is a substantial driver of attitude towards a website (Lustria 2007). Users form more favorable attitudes when they draw their own conclusions from the stimuli compared to less effortful explicit conclusions provided with the stimuli (Botti and Iyengar 2004). On the other hand, on an online learning environment, higher levels of active interaction with the instructor or the system are related to higher satisfaction and evaluation of the online medium (Arbaugh and Benbunan-Fich 2007). The reason is that taking control of the learning experience can increase the user's self-efficacy. Therefore, the inferiority of passive interaction is expected to be mediated by the decreased content learning expected from more passive personalization interaction. Users feel more engaged and motivated when a website creates a dynamic environment with high interaction and consequently they are likely to form a more complete perception of the usefulness of the website (Jiang and Benbasat 2005; Jiang and Benbasat 2007a). We expect that even though passive personalization interaction requires less effort from the users—which in itself may have a positive direct effect on website evaluation and intention to revisit a website—its effect on content learning is highly negative which in turn decreases website evaluation and intention to revisit.

User involvement can also lead to the creation of a relatively stronger bond with the provider. This bond can be achieved in active personalization interaction conditions where users control the information search experience (Ariely 2000). The reason is that taking control of the experience can increase the user's self-efficacy and can lead to a stronger feeling of involvement (Jiang and Benbasat 2007a). Perceived control is positively linked to intention to return to a website (Koufaris 2002). In addition, it has been proposed that, effective learning can serve as a strong mediator of further behavior (Suh and Lee 2005). Therefore it is expected that even though process personalization offers quicker and less effortful task completion (which in itself is expected to be a positive effect), the fact that users' involvement is lower also leads to less learning and which has the opposite effect. More specifically, we expect intention for future usage to also at least partly depend on the amount of learning (Xiao and Benbasat 2007).

- **Hypothesis 4b.** *Content learning mediates the negative effect of passive personalization interaction on website evaluation.*
- **Hypothesis 4c.** *Content learning mediates the negative effect of passive personalization interaction on intention to revisit the website.*

Figure 2 summarizes our hypotheses and conceptual model. Additionally, in our conceptual model we include the effect of website evaluation on consumers' intention to return to the website (Bhattacherjee 2001; Jiang and Benbasat 2007a).

Figure 2. Information Personalization and Content Learning: A Mediation Model



4. METHODOLOGY

To test the effects of information provision across different levels of effort within personalization, we conducted two experimental studies where participants were asked to visit a content-based website and acquire the necessary information based on a given scenario. In the first study, we first test the effects of content learning regarding users' behavioral outcomes. We investigate if information personalization leads to favorable behavioral outcomes and is mediated by the amount of content learning. We used a single factor design with two dimensions (personalized information versus generic information). In the second study, we distinguish between personalization content and personalization interaction, and examine the effects of both dimensions on behavioral outcomes of the users mediated by content learning. We used a 2 × 2 factorial design with personalization content (high versus low) and personalization interaction (high versus low).

We used a health information website because of its information rich environment and its requirement on information personalization. In such a way, we could control for product related factors that could influence our structurally proposed relationships (such as brand influence or product attributes). There is also an increasing number of online users access health related information. Also, the digital transformation of healthcare management places the industry in the limelight of interest from an IS perspective (Agarwal et al 2010). For both studies, we used the medical website www.webmd.com for two reasons. First, it is one of the most visited health websites worldwide. Therefore, we could control for unfavorable behavioral outcomes of the users due to the bad quality of the website. Second, the website offers a variety of information personalization approaches as well as generic, non-personalized information, thus providing a natural experimental setting for us.

4.1. Study 1: The Effect of Information Personalization vs. Generic Information

Study Design. The purpose of this study was to investigate the effects of information personalization compared to providing generic information and in particular to examine the role of content learning within this context. In the study participants were presented with a hypothetical scenario describing a realistic health issue. More specifically, participants were given a list of symptoms. They were asked to imagine they experienced these symptoms and to actually visit the website to find more information about the most relevant health issues so that they would be able to identify them as well as the most appropriate treatment and medication. In the personalized information condition we used a form of personalization that is popular among websites and substantially reduces the effort needed by the users since it resembles a full service approach, where users received personalized and condensed information from the website. In the generic information condition participants received a generic list with the most visited health topics in the website, where the health conditions in the scenario were picked from. The detailed manipulations for the two experimental conditions can be found in Table 1.

Experimental Procedure. At the beginning, participants were introduced to the task and were given explanations about the procedure. In the first part of the experiment participants were asked to visit the www.webmd.com website and browse through the different sections to ensure an equal level of website efficacy across participants. Participants were randomly assigned to a personalized or generic information condition. They were asked to use the website to find specific information related to health condition described in a scenario. We ensured that participants were not able to visit any other website during the experiment. After completing the required task, participants had to do a memory recall test to measure the amount of content learning that had taken place. This was followed by several questions asking them to evaluate the website's quality and to express their intention to revisit the website in case of a future need for health information. The layouts of the website used in the experiment are shown in Figure 3.

Measurement of Constructs. We summarized the items used to measure the proposed constructs in the conceptual model in Table 2.

Personalization Condition. Personalization condition was measured by a binary variable.

Content Learning. Recall from memory is found to be a relatively good proxy of the actual objective knowledge and learning (Kanwar et al. 1990; Khalifa and Lam 2002; Suh and Lee 2005). Thus, we measured content learning based on an aided recall accuracy test. More specifically, we measured it as the percentage of questions correctly answered.

Website Evaluation. Many studies measured the effectiveness of an information system in terms of quality aspects (Bailey and Pearson 1983; DeLone and McLean 1992; Doll and Torkzadeh 1988). The level of quality that a website offers can capture users' satisfaction. DeLone and McLean (1992) measured information and system quality as separate constructs.

We developed a composite measurement consisting of five factors, namely, content, accuracy, format, ease of use and timeliness. These distinct drivers of quality then form a second order construct of website end-user satisfaction (Abdinnour-Helm et al. 2005; Bailey and Pearson 1983; Doll and Torkzadeh 1988). The measurement items used were developed based on scales found in the literature and were adapted based on our empirical context. Some items were adjusted for study 2 compared to study 1 based on prior literature (Wang and Strong 1996). All items were measured using a 1-7 Likert scale.

Intention to Revisit. To measure the intention to revisit the website, we asked people's likelihood of revisiting the same website in case they have medical needs using a 1-7 Likert scale. The decision to use a single item is based on its predictive validity (Bergkvist and Rossiter 2007) as well as the consideration of effort reduction required with answering multiple questions.

Table 1. Manipulations of Independent Variables

Study 1: The Effect of Information Personalization vs. Generic Information
Information Personalization: Participants were asked to visit the website to search for information based on a given scenario. In the *personalized condition*, participants had access to information tailored based on the core of the health issue related to the scenario. We used this approach because we expect it to minimize the effort and is used often by online information providers. In the *generic information condition*, participants were asked to visit the same website and to find the requested information by using listed generic information in the form of the most popular health conditions. The information related to the given scenario was identical in both conditions.
Study 2: The Effect of Personalization Content vs. Personalization Interaction
Personalization Content: Participants were asked to visit the website to search for information based on a given scenario. Two conditions were used based on the amount of effort required by participants to process the content of the information found. In the *extensive personalization content condition (high effort)*, the information acquired was an approximately 1000 words document related to

the health condition. In the *focused personalization content condition (low effort)*, the informational outcome was an approximately 200 words document with condensed information concerning the health issue. *Personalization Interaction*: Participants were asked to visit the website to search for information based on a given scenario. Two conditions were used based on the amount of effort in interaction required from participants in the process of information search. In the *active personalization interaction condition (high effort)*, participants were asked to interact with the website and evaluate on their own the outcomes before choosing the most appropriate information. In the *passive personalization interaction condition (low effort)*, participants used a less interactive process to find the information. After requesting an answer from an expert from the website, users, without having to search, received a document with information about the health condition that best fits the symptoms of the scenario. The information used in the passive condition was identical to the information users could find on the website in the active condition. This allows us to control for the quality of the information.

Table 2. Measurement and Items

Personalization Conditions: We used binary coding for personalization conditions. In Study 1, we coded Personalized Information variable as 0 for generic information and 1 for personalized information. In Study 2, we used the variables Personalization Content and Personalization Interaction for the personalization dimensions. The value of 1 corresponds to lower effort needed in the respective dimension (i.e. the greater personalization case). More specifically, Personalization Content has the value of 1 for the focused condition, and Personalization Interaction has the value of 1 for the passive condition.			
Content Learning: 20 multiple choice questions including multiple answers. Final score was based on the percentage of correctly chosen answers.			
Website Evaluation: Thinking back about the website you visited / information you got from the website, please state the degree of agreement with the following statements.			
First Level Factors	**Code**	**Item**	**Source**
Content	C1	The information I found on ______ is precise.	(1, 2)
	C2	The information I found on ______ is of high quality.	(3, 4)
	C3	The information I found on ______ covers my needs.	(1, 2)
	C4	The information I found on ______ is complete.	(1, 2)
Accuracy	A1	The information I found on ______ is reliable.	(5)
	A2*	The information I found on ______ is valid.	(5)
	A3**	The information I found on ______ is accurate.	(1, 2)

Format	F1	The information I found on ______ is clear.	(1, 2)
	F2*	The information is presented in a satisfactory way.	(1, 2)
	F3**	The website is well organized.	(6)
	F4**	The website is well formatted.	(6)
Ease of Use	E1	The website is easy / complex to use.	(1, 2)
	E2	The website gives easy access to information.	(3, 4)
Timeliness	T1	The website gives quick access to information.	(1, 2)
	T2	The information I found on ______ is up-to-date.	(1, 2)
Intention to Revisit: If you had a future need for health related information, how likely would you consider visiting www.webmd.com?			
Note 1: *used only in study 1; **used only in study 2 Note 2: (1) Abdinnour-Helm et al. (2005); (2) Doll and Torkzadeh (1988); (3) Nelson et al. (2005); (4) Wixom and Todd (2005); (5) Zmud (1978); (6) Wang and Strong (1996)			

4.2. Study 2: The Effect of Personalization Content vs. Personalization Interaction

Study Design. In the second experiment, we disentangled the effects of personalization content and personalization interaction. In the first study, we investigated whether high information personalization, which minimizes the effort, is beneficial compared to generic information. In the second study, we demonstrated that decreasing the effort does not have the same effect across the two dimensions. Participants visited the same website as in Study 1 and again based on the same hypothetical scenario were asked to search for information. The stimuli were designed based on the dimensions of high and low effort personalization content and interaction. The detailed manipulations can be found in Table 1.

Experimental Procedure. The overall task was similar to the first study. In the introduction participants were given explanations about the procedure. Participants were randomly assigned to an experimental condition: active vs. passive personalization interaction (high vs. low effort) and extensive vs. focused personalization content (high vs. low effort). Participants were asked to use the website to acquire the information needed to identify the health condition described in the scenario, as well as possible treatments. After completing the task, participants were asked to take a recall test (to measure content learning) and evaluate the website as well as their website continuance intention. An illustration of the layouts of the website is shown in Figure 3.

5. DATA ANALYSIS AND FINDINGS

The results from Study 1 are used to test H1a, H1b, and H2a to H2c. The results from Study 2 are used to test H3a to H3c, and H4a to H4c related to personalization content and interaction and to further confirm the findings from Study 1 regarding H1a and H1b.

5.1. Results of Study 1

A total sample of 121 students from the business school of a major university in the Netherlands participated in this study. All participants were given academic credits for their participation. They were randomly assigned to whether a personalized or a generic information condition (61 and 60 participants respectively). In total there were 61 males and 60 females, and their average age was 21.3. We summarize the participants' characteristics in Table 3.

Manipulation Check. To check for the manipulation of personalization, we compared the effort needed to search for the information needed based on given scenarios. To measure effort, the level of information search is frequently used as an indicator (Bettman et al. 1993). Personalized service is expected to reduce the effort needed in a given search task, thus time spent in searching is a good proxy for effort spent (Bettman et al. 1990). Therefore, by comparing the time needed to find and process the information, we expect a significantly lesser time needed in the personalized condition compared to the generic information condition. The results showed that the average time needed to find and process the information needed in the personalized information condition (140 seconds) was significantly smaller than that in the generic information condition (423 seconds) ($t=84.96$, $p<0.01$), suggesting a successful manipulation of the personalization conditions.

Table 3. Participant Characteristics

Participants Characteristics	Study 1		Study 2	
Age	21.3 (2.3)*		21.4 (2.6)*	
Gender	Male	50.4%	Male	52.6%
	Female	49.6%	Female	47.4%
Education	Bachelor	65.3%	Bachelor	64.7%
	Master	28.1%	Master	30.5%
	Other	6.6%	Other	4.8%
Internet Experience (Years of Internet use)	< 6 years	59.5%	< 6 years	59.1%
	>= 6 years	40.5%	> 6 years	41.0%
Frequency of use (Hours per week)	< 20 hours	38.0%	< 20 hours	37.3%
	>= 20 hours	62.0%	>= 20 hours	62.6%
Have you ever visited the website?	No	97.5%	No	95.6%
	Yes	2.5%	Yes	4.4%
Have searched for online health information before?	No	10.7%	No	10.0%
	Yes	89.3%	Yes	90.0%
Number of Participants	121		249	

* mean (standard deviation)

Measurement Model. We tested the hypotheses using partial least squares (PLS) with SmartPLS (Ringle et al. 2005). The interrelations between the constructs used in our conceptual model rendered the use of a more structural model necessary (Wetzels et al. 2009, Au et al. 2008). PLS was chosen due to the high flexibility and statistical power regarding theory building (Hair et al 2011). First, we constructed the first order latent variables and then related these factors to the second order factor of website evaluation (Abdinnour-Helm et al. 2005). Second, we assessed the convergent and discriminant validity of the first order latent factors (Bollen 1989). The validity and reliability of the constructs were evaluated based on composite reliability (CR), average variance extracted (AVE) and Cronbach's Alphas. We found that the variation explained in the *timeliness* factor was low (Cronbach's Alpha<0.5), which undermined the overall validity of the second order factor of website evaluation (AVE<0.5). It also showed the same problematic behavior in website end-user computing satisfaction scale. Thus we decided to drop this factor for further analysis based on Abdinnour-Helm et al. (2005).

We summarize the results in Table 4 and 5. The results show that in the first order model Cronbach's Alphas were all above the suggested threshold of 0.7 for acceptable reliability

(Gefen et al. 2000). Moreover, all AVE values were above the recommended value of 0.50. Finally, factor analysis showed that all the items loaded sufficiently in the expected constructs. In order to test the discriminant validity of our structural model, we computed the square root of the AVEs and compared them with the correlations between the constructs, indicating that more variance was shared between the construct and its indicators than with other constructs. The results show that all the AVEs' square roots were greater than the correlations among constructs, suggesting that all the constructs had satisfactory discriminant validity.

In the second order model, all reliability measures exceeded the respective acceptable thresholds and all latent variables were highly loaded onto the higher order construct of website evaluation. Also, we measured the goodness of fit of our model and obtained 0.74 (Tenenhaus et al. 2005), indicating good performance of our model.

Table 4. Assessing the Hierarchical Model of Website Evaluation

Hierarchical First-Order Model				
	Content	**Accuracy**	**Format**	**Ease of Use**
CR	0.88	0.95	0.86	0.88
AVE	0.65	0.90	0.76	0.79
Cronbach's Alpha	0.82	0.89	0.69	0.73
C1	**0.83****	0.51	0.59	0.53
C2	**0.80****	0.56	0.47	0.49
C3	**0.80****	0.50	0.61	0.47
C4	**0.80****	0.50	0.40	0.45
A1	0.59	**0.95****	0.48	0.48
A2	0.63	**0.95****	0.61	0.53
F1	0.54	0.44	**0.86****	0.56
F2	0.59	0.56	**0.88****	0.55
E1	0.51	0.44	0.50	**0.88****
E2	0.55	0.50	0.62	**0.90****

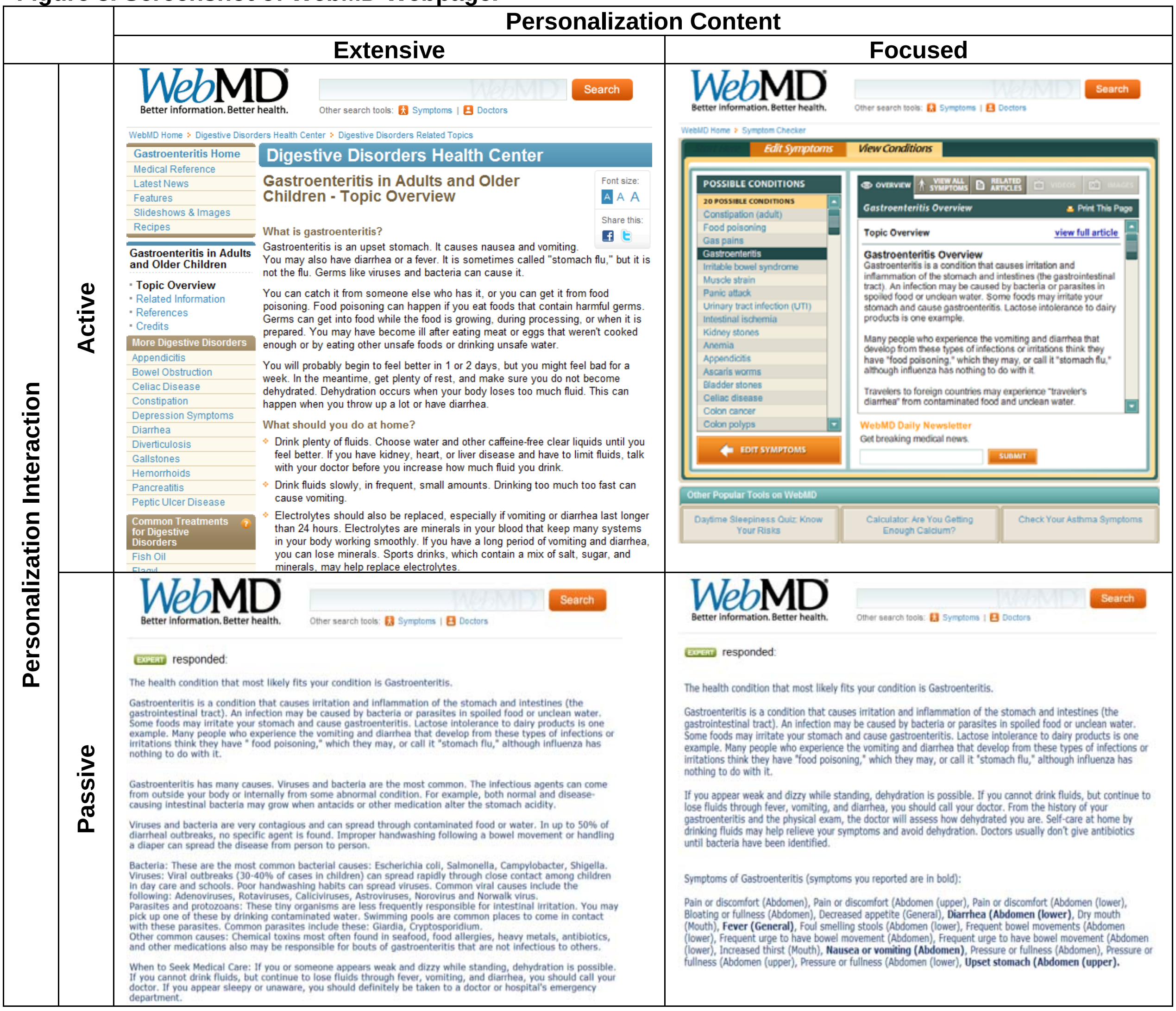
Hierarchical Second-Order Model		
	Website Evaluation	
CR	0.92	
AVE	0.54	
Cronbach's Alpha	0.90	
Content	0.90**	Loadings of the first-order latent factors on the second-order factor
Accuracy	0.82**	
Ease of Use	0.80**	
Format	0.83**	
Note: Model fit = 0.74; CR: Composite Reliability; AVE: Average Variance Extracted; **p < 0.01		

Table 5. Intercorrelations of the Latent Variables for First-Order Constructs

	Accuracy	Content	Ease of Use	Format
Accuracy	**0.95**			
Content	0.65	**0.81**		
Ease of Use	0.54	0.61	**0.89**	
Format	0.58	0.65	0.64	**0.87**

*Square root of the AVE on the diagonal

Figure 3. Screenshot of WebMD Webpage.



Structural Model. We measured the significance of the relationships between our independent and dependent variables (see Figure 4). The model accounted for 36.5% of the variance of intention to revisit and 20.2% of the website evaluation, which is moderate (Chin 1998). The results of this study provide strong support for the respective hypotheses.

We first tested the effects of content learning on behavioral outcomes. Higher content learning has a positive and significant influence on both the website evaluation ($\beta=0.43$, $t=9.85$, $p<0.01$) and the intention to revisit the website ($\beta=0.43$, $t=10.98$, $p<0.01$). Therefore, H1a and H1b are supported. We then considered the direct effects of information personalization on content learning. Results showed that information personalization leads to higher learning ($\beta=0.27$, $t=6.87$, $p<0.01$), giving support to H2a. To test H2b and H2c regarding the mediation effect of content learning, we followed the three-step procedure proposed by Baron and Kenny (1986). An overview of the mediation test results is presented in Table 6. We first found a significant effect of the independent variable (information personalization) on the mediator (content learning) and, second, we found a significant effect of the mediator (content learning) on the dependent variables (website evaluation and intention to revisit) (see results for H1a, H1b and H2a). The third step is to examine the effects of the independent variable on the dependent variable with and without the presence of the mediator. The direct effects of information personalization on website evaluation ($\beta=0.19$, $t=4.23$, $p<0.01$) as well as on the intention to revisit the website ($\beta=0.20$, $t=4.81$, $p<0.01$) are positive and significant. When controlling for the amount of content learning, these effects disappeared which suggests full mediation. More precisely, the effect of personalized information on website evaluation became not significant ($\beta=0.07$, $t=1.47$, $p>0.05$), showing a full mediation effect. The effect on intention to revisit, when controlling for content learning, also became insignificant ($\beta=0.06$, $t=1.48$, $p>0.05$), indicating a full mediation. Therefore, H2b and H2c are confirmed.

In addition to testing the proposed hypotheses, we tested whether website evaluation operates as a further mediator of the effects of learning and information personalization on intention to revisit. A mediation analysis showed a marginal partial mediation role of website evaluation that did not affect our conclusions. Whereas website evaluation partially mediates the effect of information personalization on revisit intention, this effect can be partly attributed to the positive relationship between content learning and website evaluation. Furthermore, we tested the effects of several demographic characteristics (i.e. age, income, online experience) as potential control variables in our model and found that only previous knowledge (regarding health related content) positively relates to content learning.

Table 6. Study 1 Results for Mediation Effect

			Coefficient in Regressions				
			Step 1	Step 2	Step 3		Mediation Result
IV	M	DV	IV → DV	IV → M	IV+M → DV		
					IV	M	
Information Personalization	Content Learning	Website Evaluation	0.19**	0.27**	0.07	0.43**	Full
Information Personalization	Content Learning	Intention to revisit	0.20**	0.27**	0.06	0.43**	Full

Note 1: ** Significant at the 0.01 level; * Significant at the 0.05 level.
Note 2: IV: independent variable; M: mediator; DV: dependent variable.

5.2. Results of Study 2

A total sample of 249 students participated in Study 2. They were randomly assigned to four different versions of information provision based on personalization content (extensive vs. focused) and personalization interaction (active vs. passive). The participants' characteristics can be found in Table 3.

Manipulation Check. The two dimensions of personalization used in this study were incorporated in the experiment by allowing access to different functionalities in the website. The distinction within each dimension depends on the effort needed by users. In order to capture this difference within each dimension, similarly to Study 1, we again registered the time spent searching and processing the information as a proxy for effort (Bettman et al. 1990). The results showed that the average time needed in the extensive (high effort) personalization content condition (351 seconds) was significantly higher than that in the focused (low effort) personalization content condition (291 seconds) ($t=5.35$, $p<0.05$). Thus, the manipulation of personalization content was successful. Similarly, for personalization interaction, the results showed that the average time needed (in seconds) to find and process the information in the active (high effort) personalization interaction condition (547 seconds) was significantly higher than that in the passive (low effort) personalization interaction condition (227 seconds) ($t=180.31$, $p<0.01$), indicating a successful manipulation.

Measurement Model. Similarly to Study 1, we assessed the convergent validity of our model was based on the reliability of items and constructs, AVE, and factor analysis. The results are summarized in Table 7 and 8. In the first order model, all reliability measures were above the respective acceptable thresholds (Gefen et al. 2000). Also, factor analysis showed that all the items loaded sufficiently on the expected constructs. In the second order model, all reliability measures exceeded the respective acceptable thresholds and all latent variables were highly loaded onto the higher order construct of website evaluation (Table 7). Model fit was 0.73, indicating good model performance.

Table 7. Study 2 Assessing the Hierarchical model of website evaluation

Hierarchical First-Order Model				
	Content	**Accuracy**	**Format**	**Ease of Use**
CR	0.89	0.89	0.84	0.90
AVE	0.67	0.79	0.63	0.82
Cronbach's Alpha	0.83	0.74	0.71	0.78
C1	**0.84****	0.68	0.53	0.45
C2	**0.80****	0.69	0.55	0.47
C3	**0.82****	0.59	0.55	0.45
C4	**0.82****	0.60	0.40	0.32
A1	0.62	**0.87****	0.46	0.39
A3	0.76	**0.91****	0.57	0.54
F1	0.62	0.58	**0.81****	0.48
F3	0.44	0.44	**0.81****	0.70
F4	0.41	0.34	**0.76****	0.50
E1	0.46	0.49	0.67	**0.91****
E2	0.49	0.46	0.59	**0.90****

Hierarchical Second-Order Model		
	Website Evaluation	
CR	**0.92**	
AVE	**0.52**	
Cronbach's Alpha	**0.91**	
Content	**0.90****	Loadings of the first-order latent factors on the second-order factor
Accuracy	**0.86****	
Ease of Use	**0.78****	
Format	**0.85****	
Note: Model fit = 0.73; CR: Composite Reliability; AVE: Average Variance Extracted; **p < 0.01		

Table 8. Study 2 Intercorrelations of the latent variables for First-Order Constructs

	Accuracy	Content	Ease of Use	Format
Accuracy	**0.89**			
Content	0.79	**0.82**		
Ease of Use	0.52	0.52	**0.90**	
Format	0.58	0.63	0.70	**0.80**

*Square root of the AVE on the diagonal

Structural Model. The results showed that the model accounted for around 40% of the variance regarding website evaluation and 50% of the variance for intention to revisit the website. First, we tested the direct effect of personalization content on content learning (see Figure 4). The focused (low effort) personalization content has a significant and positive effect on content learning (β=0.19, t=4.57, p<0.05), confirming H3a. Second, we tested the direct effect of passive (low effort) personalization interaction on content learning and found a significant negative effect (β=-0.37, t=10.47, p<0.05), confirming H4a.

Similar to Study 1, we followed the three-step approach of Baron and Kenny (1986) to test the mediation effect. In the first step, we found that regarding personalization content, decreasing the effort needed due to more focused content leads to significantly higher website evaluation (β=0.09, t=1.99, p<0.05) as well as higher intention to revisit the website (β=0.15, t=3.64, p<0.01). Regarding personalization interaction, decreasing the effort needed by the users by taking all control of the interaction from the users leads to significantly lower website evaluation (β=-0.13, t=3.13, p<0.01) as well as intention to revisit the website (β=-0.31, t=8.27, p<0.01). In the second step, we found that decreasing the effort regarding personalization content (focused) increases learning whereas the respective effect regarding personalization interaction (passive) has the opposite effect on content learning. Also, we examined the effect of content learning on the behavioral outcomes and whether the mediating role of content learning also holds after disentangling information personalization. The results show that content learning significantly increases both website evaluation ($\beta=0.67$, $t=21.18$, $p<0.05$) and intention to revisit the website ($\beta=0.31$, $t=6.31$, $p<0.05$), giving us further confirmation for the support of hypotheses 1a and 1b respectively. Furthermore, we find that regarding personalization content, by controlling for content learning in the model, both effects on website evaluation ($\beta=-0.04$, $t=1.02$, $p>0.05$) and intention to revisit ($\beta=0.06$, $t=1.83$, $p>0.05$) became insignificant, showing full mediation. Therefore, H3b and H3c are supported. Regarding personalization interaction, by including content learning, we found that the effect of low effort personalization interaction on website evaluation becomes positive ($\beta=0.11$, $t=3.02$, $p<0.01$). This is in line with our expectation that less effort in itself positively influences the evaluation of the website, but shows that in our data the net effect of greater personalization interaction is negative which can be explained by its negative effect on content learning. The effect of personalization interaction on intention to revisit the website, when controlling for content learning, became weaker ($\beta=-0.15$, $t=4.03$, $p<0.01$), showing partial mediation. As a result, H4b and H4c are supported. A detailed description of the mediation results can be found in Table 9. We summarize all hypotheses testing results in Figure 4 and Table 10.

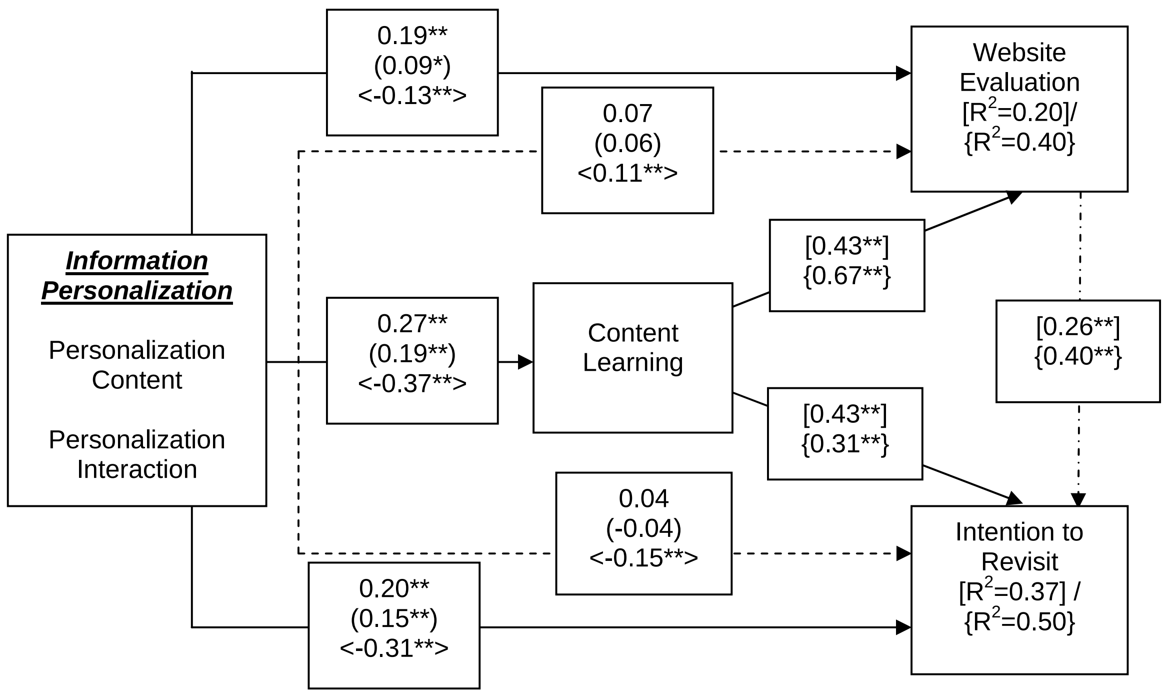
Finally, we tested whether website evaluation plays a mediating role towards intention to revisit the website. An additional mediation analysis showed a marginal partial mediation effect regarding the effects of personalization dimensions and content learning on intention to revisit the website. This effect can be mainly attributed to the high correlation between website evaluation and content learning. We controlled for possible effects of demographic characteristics and, similar to study 1, only previous health related knowledge has a significant positive effect on content learning (however with the inclusion of these variables, our conclusions remain consistent.

Table 9. Study 2 Results for Mediation Effect

			Coefficient in Regressions				
			Step 1	**Step 2**	**Step 3**		**Mediation Result**
IV	**M**	**DV**	**IV->DV**	**IV->M**	**IV+M->DV**		
					IV	**M**	
Focused	CL	WE	0.09*	0.19**	-0.04	0.67**	Full
Focused	CL	IR	0.15**	0.19**	0.06	0.58**	Full
Passive	CL	WE	-0.13**	-0.39**	0.11**	0.67**	Full
Passive	CL	IR	-0.31**	-0.39**	-0.15**	0.58**	Partial

Note 1: ** Significant at the 0.01 level; * Significant at the 0.05 level
Note 2: IV: independent variable; M: mediator; DV: dependent variable.
Note 3: Focused: Low effort personalization content, Passive: Low effort personalization interaction, CL: Content learning, IR: Intention to revisit, WE: Website Evaluation

Figure 4. Summary of Results in Structural Model



Note 1: For effect of Information Personalization:
Study 1: no brackets – Information personalization vs. Generic information,
Study 2: (Focused low effort vs. Extensive high effort Personalization content), < Passive low effort vs. Active high effort personalization interaction >
Note 2: For effect of learning: [study 1], {study 2}
Note 3: ** Significant at the 0.01 level; * Significant at the 0.05 level

Note 4: → Direct effect.
- - -▸ Effect when Content learning is included.
-·-·-▸ Not specifically hypothesized but path included for statistical testing.

Table 10. Summary of Hypotheses Testing Results

	Hypotheses	Result
1a	Greater content learning on a website increases the website evaluation	Supported
1b	Higher content learning on a website increases the intention to revisit the website	Supported
2a	Offering personalized information on a website increases the website's evaluation.	Supported
2b	Content learning mediates the effect of information personalization on website evaluation.	Supported
2c	Content learning mediates the effect of information personalization on intention to revisit.	Supported
3a	More focused personalization of a website's content increases content learning.	Supported
3b	Content learning mediates the effect of personalization content on website evaluation.	Supported
3c	Content learning mediates the effect of personalization content on intention to revisit.	Supported
4a	More passive personalization of a website's content decreases content learning.	Supported
4b	Content learning mediates the effect of personalization interaction on website evaluation.	Supported
4c	Content learning mediates the effect of personalization interaction on intention to revisit.	Supported

6. DISCUSSIONS AND CONCLUSIONS

6.1 Discussions of the Findings

In this paper, we argue that content learning captures and explains the effectiveness of information personalization. Content learning has been largely neglected from the IS and marketing literature. Mittal and Sawhney (2001) suggested that learning experience can impact subsequent behavior towards a website. We proposed that content learning is an integral part of the user-website interaction and that information personalization positively influences content learning. The reason is that personalization filters out irrelevant information and therefore users are able to focus on the information they really need (Tam and Ho 2006). The results of the two studies underline the importance of information personalization and content learning in forming several behavioral outcomes in content-based websites. These findings underline our main proposition that the propitious role of information personalization is mediated by the amount of content learning.

We also show that greater information personalization by reducing the effort needed within personalization is not always beneficial because some personalization approaches despite requiring higher effort from the users have a positive effect on content learning. Thus, the effectiveness of lower effort personalization on content learning and behavioral outcomes can vary depending on the type of personalization. To explain these differences we propose that information personalization should be conceptualized in terms of two dimensions based on the effort needed from the user.

We disentangle information personalization into personalization content (outcome) and personalization interaction (process) (Suprenant and Solomon 1987). These different dimensions of information personalization can have different effects on content learning. More precisely, our results suggest that while lowering the effort with respect to personalization content increases content learning, lowering effort in the personalization interaction has the opposite effect. More personalized content of information focuses the user on the core of the information needed and bypasses any risk of overload which harms learning (Jacoby et al. 1974). Conversely, lowering the effort in personalization interaction means that the website takes control from the user in order to minimize his effort needed and therefore users receive the information delivered in a more passive way. Whereas, in principle, such an approach seems appealing to the users, we show that asking users for more effort regarding interaction, increases the amount of content learning.

Content learning significantly influences the users' behavioral outcomes after a website's use. We used the website evaluation as well as the intention to reuse the website to describe users' behavioral outcomes. Website evaluation has been closely linked to users' satisfaction as well as the quality of the website in terms of the system, information and service (DeLone and McLean 1992; Doll and Torkzadeh 1988). Moreover, since the competition in an online environment is very large and the switching barriers are relatively low compared to offline environments, retaining consumers is a very important goal for websites (Murray and Haubl 2007). In both studies our results supported our hypotheses that content learning influences all these behavioral outcomes. That is content learning positively influences the evaluation measures as well as the intention of the users to revisit the website in the future. This is consistent with goal achievement theory that argues goal achievement leads to higher degrees of satisfaction (Locke and Latham 1990). Especially in content-based websites, accessing the right information signifies the goal completion of the users who search for information. Thus, content learning increases their attitude towards the website.

In summary, while prior research in IS has examined the relationship between personalization and system evaluation (Komiak and Benbasat 2006; Tam and Ho 2006), this paper is the first to examine the role of content learning in explaining the effectiveness of information personalization. The results of the first study indicate that (1) information personalization positively influences the amount of users' content learning, and (2) content learning mediates the positive effects of information personalization on the users' behavioral outcomes. The findings of the second study show that (1) decreasing the effort regarding personalization content has positive effects on users' content learning, (2) decreasing the effort regarding the personalization interaction has negative effects on content learning and (3) content learning mediates the differential effects of the two dimensions of information personalization on users' behavioral outcomes. More specifically, when users experience a higher level of personalization content that provides more focused and relevant information can have more favorable subsequent behaviors. These effects are fully explained by the increased content learning that reduces information load. However, regarding the personalization interaction, lowering the effort required by the users has an opposite result. Though higher effort from users would lead to lower satisfaction and subsequent behaviors, active involvement can be beneficial due to increased content learning that users can achieve.

Finally, we show an interesting additional result regarding personalization interaction and website evaluation. Without taking into consideration the amount of content learning, the effect of high effort personalization interaction on website evaluation is positive, showing that users, who were actively involved in the information search, evaluated the website higher. However when controlling for content learning, this effect shows the opposite sign. We can interpret this as follows. The overall positive effect of this type of effort can be attributed to the increased content learning. When we control for that effect, the remainder is the direct effect of effort, which is undesirable for users (Bettman et al. 1990). More practically, when users achieve the same levels of content learning, their evaluation would be higher when the effort needed was lower.

6.2. Theoretical Contributions

Personalization strategies and their effectiveness have received a lot of attention in the literature in both IS (Komiak and Benbasat 2006; Tam and Ho 2006) and marketing (Ansari and Mela 2003; Murray and Haubl 2007). The current study contributes to this literature in a number of ways.

First, different from past research that treats information personalization as a singular construct (Murray and Haubl 2007; Tam and Ho 2006), in this paper we disentangle information personalization into two distinct dimensions, namely personalization content and personalization interaction, related respectively to the outcome and the process of personalization. This distinction also relates to the different levels of effort endured by the users in information personalization. This is different from prior research that mainly considers different dimensions as a means of characterizing the personalization, for example, option versus programmed personalization (Suprenant and Solomon 1987), or information versus navigation personalization (Wang and Yen 2010). We show that user effort can be reduced with information personalization in two ways. First, it reduces user effort by providing tailored content based on user needs and, second, by personalizing the way the personalized content is retrieved by users (capturing the way in which users interactively engage with the website). In addition, our results suggest that both personalization dimensions influence the effectiveness of a website, since they can reduce the information load required from users.

Second, in this study, we propose theoretically and test empirically the role of content learning in information personalization and its impact on users' behavioral outcomes. In addition, we also demonstrate how content learning influences personalization content and personalization interaction in a different manner. Content learning has been introduced in cognitive psychology as the link between the informational stimuli that is accessed and the subsequent behavioral response to the stimuli (Shuell 1986; Vandenbosch and Higgins 1996). From a similar perspective, cognitive performance in an educational context is crucial for the learner's behavioral disposition (Cordova and Lepper 1996; Khalifa and Lam 2002). Previous studies relating learning to personalization have primarily focused on interface processes and the acquisition of skills that could lead to a state of lock-in due to cognitive barriers (Murray and Haubl 2002). Content learning has been largely neglected, though past studies have agreed that the effectiveness of system depends on the performance of the learners in terms of achievement and recall (Mittal and Sawhney 2001; Piccoli et al. 2001). In this paper, we propose that content learning plays a greater role in personalization, and relates to the declarative level of knowledge formation that the user succeeds (Smith 1990). We highlight the importance of content learning in positively influencing the behavioral responses of website users. The amount of information that users learn in a website can signify their individual performance which, in turn, can influence their attitude towards the website (Dabholkar and Bagozzi 2002). Additionally, this paper highlights the central role of content learning in the implementation of personalization technologies.

Third, this study provides a framework that illustrates a mechanism through which information personalization can be improved. We argue that greater personalization is not always beneficial. Although analogous claims can be found in the literature (mainly related to privacy and control issues), in this study we propose that the basis for this underperformance can be related to the concepts of user effort and content learning (Awad and Krshnan 2006; Shen and Ball 2009). Our findings imply that offering personalized information can increase the performance of the user and can decrease the effort needed when searching for information compared to offering generic information to the users. However, the effect is not equally beneficial for different types of personalization. We show that while decreasing the effort of personalization content is beneficial for the website, the same approach toward personalization interaction diminishes these effects. The results imply that a more personalized service is not always better even though the required effort from the users is lower. The underlying reason is that more effort may be related to increased content learning which we show that is a substantial driver of user response towards the website. This finding is consistent with studies related to self-service technologies and their positive effects on behavioral outcomes of the users despite the increased effort needed (Dabholkar and Bagozzi 2002; Meuter et al. 2000).

Finally, this research also augments the findings of past literature related to content-based websites in general. Prior research on news or health information websites, where information is the main offering of their service, has typically focused on website evaluations (Huizingh 2000; Quelch and Klein 1996). Other studies on online information search behavior have focused on pre-purchase information searches on transactional websites and investigated website conversion (Johnson et al. 2003; Mittal and Sawhney 2001). However, augmenting to the previous research in this area, our paper provides empirical evidence of the importance of offering personalized services in improving users' returns. This is particularly essential for content-based service providers, because these firms need to obtain a substantial part of their revenues from third parties, such as advertisers, who base their decision to be advertised on a given website on the number of visits that the website receives. Further, they also face the challenge of creating a sustainable customer base in a market environment where consumers can easily find alternative offerings.

6.3. Managerial Implications

From a managerial viewpoint, this study spotlights several crucial issues for online firms. First, in the debate on whether information personalization is beneficial for users and firms, we provide further evidence for its merits. Even though information personalization requires costly investments from firms in terms of implementation as well as operationalization, an increasingly large portion of online firms in various domains introduce these technologies (Andrews and Votsch 2001; Jupiter Research 2003). Examples of such firms can be found in online news (e.g. Wall Street Journal, Yahoo), financial services or investments (e.g., Citibank credit cards, mortgage websites) and educational institutions (e.g. Northcentral University). Therefore, a better understanding of when and why information personalization is useful is very important for the success of these firms (Liu et al 2010). We show that information personalization has a clear beneficial effect regarding behavioral responses of the visitors. Users who have access to personalized information show higher website evaluation ratings as well as increased revisit intentions. We find that, depending on their specific cost structure, there is the potential for online firms to gain from the investment on personalization technologies, especially in online channels.

Second, we highlight an additional beneficial effect of information personalization by showing that personalized information increases the amount of content learning on the website. We pinpoint the role of content learning as a mediator of the effect of information personalization on the behavioral responses of the users. In line with past studies positing that learning is the link between stimuli and behavior (Shuell 1986; Vandenbosch and Higgins 1996), we show that the beneficial effects of personalization are explained by the amount of information that users learn. Online firms can benefit from these results, since they may improve the returns on the vast investment in personalization technologies, by making the process of content learning on their websites easier to their users. We give guidance for online firms to better regulate their retention strategies and approaches and take even more advantage of the personalization technologies. To our knowledge, behavioral responses towards a website have not been linked to content learning. Our results suggest that by neglecting content learning, websites can lose customers by not being able to facilitate their learning, leading to suboptimal performance and decreased customer satisfaction. Past studies have showed that whereas personalization is widely adopted by online firms, only a small amount attributes their repeating visitation to personalization. We show that these contradictory indications can be further attributed to the neglect of information providers to facilitate the process of content learning through their systems. One way to encourage such an increased level of content learning can be achieved by websites by implementing content that can be rapidly apprehended by their users.

Third, our study shows that achieving effective information personalization is not a one dimensional endeavor. We distinguish between two discrete dimensions of information personalization, showing that this distinction is of high importance and relevance for online managers since it gives a more structured view of the mechanism of personalization. Based on our results, websites can manipulate their personalization approach based on the amount of user effort needed regarding the outcome (content) and the process (interaction) of information personalization. Taking into account the role of content learning, we show that different types of personalization may lead to different system performance and user satisfaction. Online firms work hard on finding ways to assist their users and to make their navigation easier and more effortless. By introducing the two dimensions of personalization, we can explain some of the debatable findings regarding the benefits of information personalization (Jupiter Research 2003; Parisier 2011). Especially in the case of content-based websites, online managers should not focus only to make the websites attractive and easy to use. Our results suggest that reducing the effort needed by the users is not always beneficial and that by taking all control away from the users and providing them with a fully personalized service, though it may seem attractive to them, does not necessarily lead to more beneficial user behavioral responses. On the contrary, we show that even an increase in the complexity and effort needed by the users, might have beneficial effects for the behavioral outcomes towards the website. It is therefore important for online information providers to be aware of the options when using personalization services to increase user learning. They may consider providing more personalized content but giving more control to the users to generate higher learning benefits. In addition, since heterogeneity across users exists (even within a given website), a one-size-fits-all approach may not be necessarily viable. Based on our personalization distinctions, websites can also offer the control of choosing the personalization approach to its users.

Finally, from a managerial standpoint, in many domains such as financial services and healthcare, where complex products are sold, companies are increasingly held accountable for ensuring that their consumers understanding of the company's offerings. Firms can improve consumers' understanding of their offers by improving the knowledge of their customers through the online content that they offer. The joint effort of consumer learning and company learning can significantly improve consumer purchase decisions, which in turn drives consumers' repeat visits. Thus, a deeper understanding of how to increase the understanding of the customers is crucial.

6.3. Limitations and Future Research

We discuss three limitations of this study and some avenues for future research. First, whereas we show that within information personalization higher effort can have beneficial effects for the website and the user, the question whether users would select these "higher effort" interfaces to begin with is still open. The important question is not merely whether a certain (more active) personalization approach can lead to higher effectiveness if used but, also, whether users will select it when also given the option of a more passive personalization approach (Ariely 2000). Therefore, it would be interesting to investigate what makes users choose among different personalization formats that differ in terms of required effort. The intention to revisit results from our studies showed that users would more likely choose low effort personalization content and high effort personalization interaction in the same website in the future. Some additional evidence in this direction has come from work on optimal stopping rules (Browne et al. 2007), which demonstrated that under conditions that allow free search, people examine considerable amounts of information before they reach a point at which they feel they have sufficient information to make a decision. In addition, the ability to command a situation, that is, having control over its different aspects, has been shown to increase the pleasure of the event itself (Shapiro et al. 1996) and the feeling of ownership over the outcome of the process. Understanding such motivational factors is very important, because in the long run they will determine consumers' desire to fully utilize interactive and electronic communication channels.

Second, we recognize the limitations of using recall for operationalizing content learning, though recall tests have also been used as a proxy for learning by prior studies (Kanwar et al. 1990). The reason is that recall is more related to short-term memory effect whereas learning is a more long term construct (Park et al. 1994). One way to overcome this problem is to repeat a recall test, a few days after the initial test, to capture in a deeper degree the intrinsic content learning. However, the complication of this approach could be that the recall test may be too long for the participants. Also, the fact that the recall test was based on multiple choice questions may make users remember more information by triggering them with the answers. However, since every subject had to take the same test, possible effects of overload in the test are canceled out. An alternative approach would be to use open ended questions to measure the effectiveness of the different conditions. Lastly, another approach that could be used is the subjective knowledge which is more related to the self-efficacy of the users and might influence their behavioral outcomes (Bandura 1997; Park et al. 1994).

Third, regarding personalization content we draw on the idea of information overload to suggest that providing extensive content to consumers is not likely to be beneficial. One potential limitation of that idea is that the effect of information load may be non-linear and that there may be more beneficial intermediate cases between the conditions we used in our study. Information overload is a subjective and heterogeneous construct across users and it would be interesting in future research to investigate if there is an empirical optimal amount of (personalization) content that can maximize learning and behavioral outcomes (Jiang and Benbasat 2007a). However, in this study we focus on the positive effect of content personalization per se (compared to no personalization) and find support for that position.

Fourth, experimental studies may not capture real life situations compared to a field study with clickstream data. Experimental studies have the advantage to control for possible covariates in the models. However, there is always the danger of biasing the results and diverting from real life situations. Future research can use clickstream data in combination with surveys in order to fully capture the performance and behavior of the website's users.

Finally, the number of respondents as well as the composition of our sample may influence our results. Our sample mainly consisted of young people. However, the use of a health information website is mostly targeted to the general population and therefore young people are not a fully representative audience. Further research can use a more generally representative sample or a different type of website.

In summary, the current work has investigated the effects of content learning in the context of information personalization. Using a distinction in operationalizing information personalization into personalization of content and personalization of the interaction, we show that information personalization is not equally beneficial across these dimensions. We show that these conflicting effects can be explained by the role of content learning. Content learning is a very important driver of evaluation measures as well as revisiting intentions and mediates the effectiveness of personalization approaches regarding the aforementioned behavioral outcomes. An improved understanding of how information personalization in websites affects the success and performance of the website is critical for online information providers (Liu et al. 2010). Our findings on how content learning mediates the differential effects of personalization on website evaluation and revisit intentions underline the conclusion that given the proliferation of personalized services online, the real question for websites is not whether to personalize or not, but rather how and how much to personalize.

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