DIMITRIOS TSEKOURAS

No Pain No Gain

The Beneficial Role of Consumer Effort in Decision-Making

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No pain no gain: gunstige effecten van inspanning
bij lastige consumenten beslissingen

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στη Μαρία

γηράσκω δ’ αιεί πολλά διδασκόμενος
“I grow old always learning many things”
Solon (638 - 558 BC)

Acknowledgements

The beginning is the end is the beginning...

This book signifies the end of an era, the finale of a big chapter in my life. A long journey that started a bit more than 5 years ago. However, this journey could not have been completed without some people I met/worked with/ encountered along the way. In this part of the book I would like to express my utmost appreciation to all of those who played a substantial role in their own unique way.

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The end is the beginning is the end...

Rotterdam, September 2012

Table of Contents

Πόνος ευκλείας πατήρ
(Much effort, much prosperity)
Euripides (480 - 406 BC)

Chapter 1
Introduction

Consumers access large amounts of information from a wide range of sources. They are able to do so since the minimized search cost has reduced the switching barriers across the variety of avilable sources. The decreased online search costs are expected to eliminate the switching barriers among providers and increase the total search across the internet (Lynch and Ariely 2000). Although there is evidence in the literature that consumers end up using only a few websites to fulfill their goals (Johnson et al. 2004), issues related to information overload still prevail and online firms still deal with low conversion rates (percentage of visits with a realized purchase) (Moe and Fader 2004)[1]. A great part of the information (content or product related) that consumers receive is not relevant to their purpose and consumers experience excessive effort (cognitive or time related) (Duan, Gu, and Whinston 2009).

According to Forrester Research, online companies encountered an approximately 13% growth in sales during 2010 and a respective stable growth rate is expected until 2015 (Carini et al. 2011; Mulpuru et al. 2011). One vital factor for this development has been the 12% increase in average order value for personalized recommendations (Siwicki 2011). The success of these recommendation agents is closely related to their competence in facilitating and making consumers' decision-making process more effective. Consumers have benefitted by decreasing their required effort and improving their decision outcomes by receiving high quality recommendations that closely match their preferences (Gretzel and Fesenmaier 2006; Häubl and Trifts 2000; Todd and Benbasat 1994; Xiao and Benbasat 2007). However, in recent business studies, only 30% of online users found the offered personalized recommendations valuable and were satisfied with the accessed content (Mulpuru et al. 2007;

[1] According to the web analytics provider Fireclick, the global conversion rate across industries since May 2011 is on average 3% (http://index.fireclick.com/fireindex.php?segment=0).

Parisier 2011). Also, many consumers would prefer to have a choice over the information (content or product related) they access (Lee and Lee 2009) even though that would signify an increased amount of required effort from them. In this dissertation, we attempt to investigate different situations or conditions under which increased consumer effort is not necessarily unfavourable for online firms.

1.1 Online Recommendation Agents

Companies aim at ensuring that their consumers fully understand the product offerings in order to ease their decision making process. This need becomes even more imperative in e-commerce where disseminating information about the products becomes more complex due to the absence of tangibility (Suh and Lee 2005). Therefore, online firms have introduced online decision aids and personalized information services (www.myproductadvisor.com). Online decision aids were introduced to deal with information overload and reduce users' required effort (Häubl and Trifts 2000). Such processes represent a very popular strategy in online content management and are widely researched in marketing (Ansari and Mela 2003; Häubl and Trifts 2000) and information systems (IS) (Awad and Krishnan 2006; Komiak and Benbasat 2006; Tam and Ho 2006). The aim is to assist consumers in finding the most relevant information by providing content based on their personal information (Chellappa and Sin 2005; Liang, Lai, and Ku 2007). One advantage of recommendation systems is that they improve the firms' efficiency and their users' accuracy and enhance consumers' decision quality (Häubl and Trifts 2000). Another important advantage of recommendation systems is the reduction of consumer effort (time spent and cognitive elaboration) needed to reach a decision (Gretzel and Fesenmaier 2006; Häubl and Trifts 2000).

1.2 Consumer Online Decision Making

The rise and distinctiveness of the online channel has substantially transformed the consumers' decision making process. Consumers' online decision making process is driven by a twofold main objective. Consumers wish to jointly maximize the accuracy of their decisions and minimize their required effort in order to achieve that level of decision quality (Bechwati and Xia 2003; Johnson and Payne 1985). Inherently, according to the principle of least effort, effort is perceived as a form of cost and therefore individuals attempt to minimize it (Liang, Lai, and Ku 2007; Zipf 1949). However, by minimizing the effort in a task, users jeopardize the quality of their decisions. This contradiction in the objectives results in trade-offs needed to be made (Todd and Benbasat 1999). From a cost versus benefits perspective, this approach is strongly related to the inherent need of decision makers that attempt to minimize their costs (effort) by maintaining their benefits (accuracy) at a maximum level (Johnson and Payne 1985).

Generally, though users would wish to proceed to an extensive assessment of available information before they reach a conclusion, this is not possible due to their time or cognitive limitations (Todd and Benbasat 1999). Without taking into account all actual limitations of consumers, one would expect that a consumer would inspect all available information until the point where she is sure about her decision. However, in an actual situation there are certain costs imposed that divert consumers' decision making process from such an extensive approach. These practical limitations refer to the cost of effort needed in order to assess all that information, either in the form of time spent or of cognitive elaboration (Todd and Benbasat 1999).

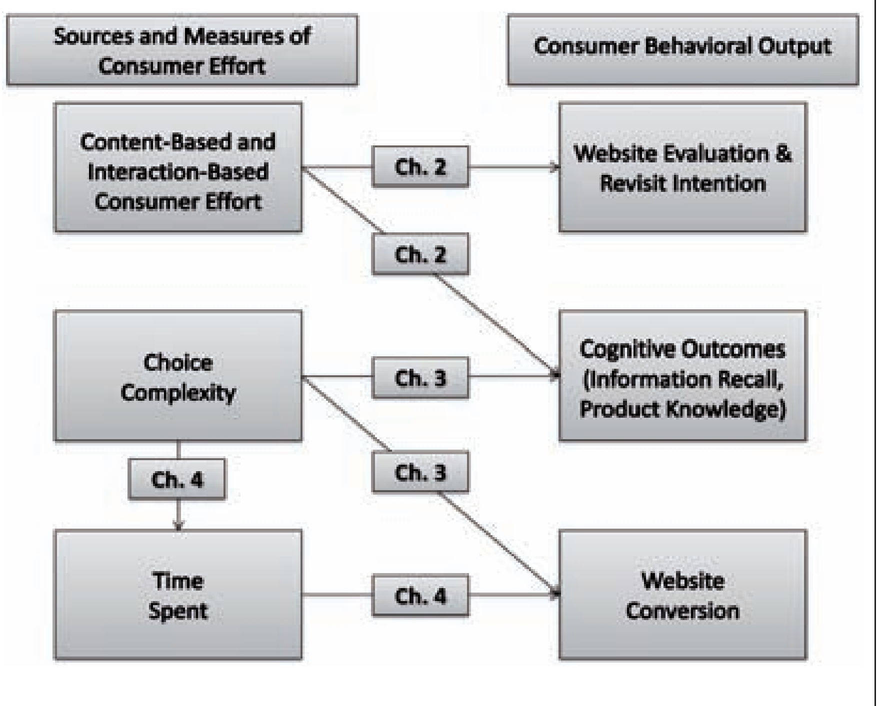
1.3 Consumer Effort

Previous research showed contradictory views on the impact of greater effort. The principle of least effort posits that effort is perceived as a form of cost for the individuals (Zipf 1949) and consumers wish to minimize their effort. Consumers are cognitive misers but at the same time they want to achieve maximum decision accuracy. Although they do not want to exert much effort in decision making they aspire to achieve high decision quality. Therefore, they welcome effort invested by others to help them decide since that would signify a higher amount of effort saving (Bechwati and Xia 2003). Prior research related to user effort reduction has emphasized its beneficial effects on the perceived quality of a decision aid as well as on system evaluation and acceptance (Häubl and Trifts 2000; Todd and Benbasat 2000).

On the other hand, various studies showed support for the effort heuristic for quality, which posits that high effort may result in higher valuation of the outcome (Cardozo 1965, Kruger et al. 2004). In addition, consumers believe that effort increases the likelihood of making a good decision (Bechwati and Xia 2003; Todd and Benbasat 2000) and as a result, the recommendation outcome is more positively evaluated (Gretzel and Fesenmaier 2006). A more complex choice increases the required effort but this effort can also be regarded as a greater investment and a signal of higher decision quality (Posheptsova, Labroo, and Dhar 2010). Also, in many cases, the amount of effort is used as a justification for the quality of the decision and based on this rationale products that are retrieved in a more difficult way may be evaluated higher because consumers want to compensate for the effort spent (Labroo and Kim 2009). The sunk-cost fallacy can explain this decision rule that often enhances the value of a future event due to past investment (Arkes and Blumer 1985).

A better understanding of the role of consumer effort may help firms that need to evaluate the benefits of making investments in their websites to increase the effectiveness of their recommendations (based on both accuracy and effort reduction) in order to justify the cost associated with implementing such an approach (Liu, Sarkar, and Sriskandarajah 2010). There are various types of risk involved in a decision making process, both regarding the outcome or the consequences of a choice (e.g. physical, financial or uncertainty risk). These types of risk are strongly related with the expected costs of a decision maker (physical, cognitive, or financial cost). Respectively, consumer effort can take different forms. Based on 3 studies, we attempt to explain the role of consumer effort by using cognitive components of microeconomic behavior. We show that consumer effort is not necessarily unfavourable and that some sources of effort can even lead to improved outcomes. The different chapters of this dissertation reflect on these different sources of consumer effort and their effects regarding various behavioral outcomes across different empirical settings (see Figure 1.1).

Figure 1.1 Dissertation Outline



1.3 Dissertation Outline

In chapter 2, we distinguish between two sources of user effort (related to information personalization), that jointly determine the likely success of effectiveness of information provision in content-based websites and suggest that user effort reduction is not necessarily beneficial. Consumer effort can be increased either by increasing the size of the informational stimuli (Malhotra 1982) or by increasing the involvement of users in the process (Hess, Fuller, and Mathew 2005). Respectively, the dimensions of information and interaction-based user effort are introduced. In addition, based on learning and goal setting theories, we argue that the success of content-based websites can be attributed to the effect of increased content learning, which is a key driver of consumers' website evaluation and revisit intention. Based on an experimental study using a health information website, we demonstrate that information-based user effort reduction, which presents focused information to the users leads to beneficial behavioral outcomes (website evaluation and revisit intention) due to the mediating role of increased content learning. However, interaction-based user effort reduction, which lowers the effort by which the information content is retrieved, has the opposite effects due to the decreased level of information retention with the user.

In chapter 3, a different source of consumer effort is introduced; choice complexity. Firms such as financial service providers are increasingly challenged to promote sufficient levels of product understanding with their customers. Traditionally, strategies to promote consumer product knowledge have focused on providing more and richer product information to consumers. However, we propose that differences in the composition of the product choice sets that are offered to consumers also affect consumer product knowledge. More specifically, we investigate the effect of choice set complexity and how it impacts objective and subjective consumer knowledge. We propose that greater choice set complexity (which signifies increased consumer effort) increases objective consumer knowledge because complex choice sets require greater cognitive elaboration on the alternatives. Conversely, greater complexity also is likely to lead to decreased consumer choice confidence and therefore we expect that it lowers subjective product knowledge. We examine the role of product knowledge in a transactional setting where product information is communicated to consumers in the form of product related recommendations. In 2 studies, we test these hypotheses using clickstream data from a financial product comparison website combined with brief online surveys, as well as data from a controlled experimental lab environment in the consumer electronics product category. The results provide support for the proposed effects of choice set complexity on consumer product knowledge. Finally, we also validate that the effect of choice set complexity on product knowledge is managerially meaningful in that it influences consumer website conversion and willingness to pay for the chosen alternative.

In chapter 4, the role of time related effort is examined in the context of online product recommendations. Marketing research results on whether firms should increase or decrease consumer online shopping inspection times to boost website conversion rates are mixed. While some studies have highlighted the positive impact of online inspection time on conversion, e.g., because more detailed inspection lowers consumer product uncertainty, others have emphasized the negative effects of inspection time due to increased consumer effort and the opportunity costs that come with it. To begin to resolve these conflicting findings this study disentangles consumer online shopping inspection time into two components that are hypothesized to have opposing effects on website conversion: choice set and product-level inspection time. We predict that at the choice set level, increases in inspection time decrease website conversion. The underlying reason is that at the choice set level, increases in time spent comparing different alternatives are determined by the complexity of the choice set, which harms conversion rates. However, at the product level we predict that increases in inspection time lead to greater website conversion. This is due to the fact that a higher product inspection time reflects a consumer's increased expected utility for that alternative, and hence has a positive impact on the likelihood of website conversion. By analyzing clickstream data from 9,473 consumers using a mortgage recommendations website, we find strong support for the proposed two opposing effects of inspection time on website conversion. The results underline the importance of disentangling total online shopping inspection time to understand and predict its effect on website conversion. Furthermore, the findings can be used to guide improvements of the composition of product choice sets that are presented to online consumers such that the sets effectively balance consumers' time spent on comparing alternatives with time spent on inspecting separate alternatives in greater details.

In sum, the overarching goal with this dissertation is to study the role of consumer effort within the context of making informed online choices. We focus on decision-making in situations where a certain level of involvement is required in order to make informed decisions. The conclusions of this dissertation are highly relevant both for academic scholars and business practitioners, but also for consumers themselves. An overview of the chapters, including the measures of consumer effort and behavioral outcomes, as well as the studies' context and data description can be found in Table 1.1.

Table 1.1 Overview of the Chapters

Chapter	Study	Sources or Measures of Consumer Effort	Behavioral Output	Context	Data
1	Introduction				
2	Learning in Content-Based Websites: The Conflicting Effect of Information versus Interaction Based User Effort	Information-based versus Interaction-based Consumer Effort	Content Learning Website Evaluation Revisit Intention	Content-Based Website (Health Portal)	Experimental study (N=249)
3	The Effects of Choice Set Complexity on Consumer Product Knowledge	Complexity of Choice Sets Composition	Objective and Subjective Product Knowledge Website Conversion Willingness to Pay	Financial Products (mortgages) / Electronics (Digital Photo Frames)	Clickstream data with online surveys (N=243) / Survey based study (N=700)
4	The Opposing Effects of Choice Set and Product Level Inspection Time on Website Conversion	Choice Set level and Product Level Inspection Time	Website Conversion	Financial Products (mortgages)	Clickstream data (N=9752)
5	Conclusion				

I hear and I forget. I see and I remember. I do and I understand.
Confucius (551 – 479 BC)

Chapter 2

Learning in Content-Based Websites: The Conflicting Effect of Information versus Interaction Based User Effort

2.1. 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[2] typically is not relevant to their purpose (Duan, Gu, and Whinston 2009). The potential downside of having access to an abundance of information is even more pressing in the case of content-based websites (i.e. news or health information websites), where users visit these websites to obtain specific information. Content-based websites receive millions of visits daily (according to www.alexa.com, the two top news and health portals receive daily on average 1,5% of total internet users) and have also gained considerable recognition (Lopes and Galetta 2006; Song and Zahedi 2007). Generally, though users would wish to proceed to an extensive assessment of available information before they reach a conclusion, this is not possible due to their time or cognitive limitations (Todd and Benbasat 1999). In order to facilitate the experience of the users, online companies have introduced online decision aids and personalized information services to help consumers reduce their required effort. Such processes represent a very popular strategy in online content management and are widely researched in marketing (Ansari and Mela 2003; Häubl and Trifts 2000; Suprenant and Solomon 1987) and information systems (IS) (Awad and Krishnan 2006; Chelappa and Sin 2005; Komiak and Benbasat 2006; Tam and Ho 2006). Information personalization is an effective way to reduce

[2] Following the DIKW Hierarchy, we define data as symbols that represent properties of objects. Information is inferred from and related to meaningful data (the actual content of relevant data available). Finally knowledge refers to processed and structured information (Rowley 2007).

consumer effort 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 and a lack of adequate user effort may signal a less sophisticated system and undermine the quality of the informational outcome. While the majority of online companies commonly use elements of personalized informational content in their interactions with their customers, there is considerable debate regarding whether these approaches increase visitor evaluations and repeat visits in these content-based websites (Aberdeen Group 2007; Jupiter Research 2003; Liu, Sarkar, and Sriskandarajah 2010). Although decision aids that reduce user effort can confront cognitive overload, they 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 the reduction of user effort (through information personalization approaches) may help content-based firms that need to evaluate the benefits of making investments in their websites to reduce user effort in order to justify the cost associated with such processes.

In this paper, we focus on the main beneficial effect of information personalization; the user effort reduction. We distinguish between two dimensions of user effort that jointly determine the likely success of effectiveness of information provision in content-based websites. (1) *Information-based user effort* refers to the information provided to the customer and more specifically the degree to which it is focused around the core information based on the specific needs of the users. The amount of offered information can vary and therefore information-based effort reduction is related to more focused and relevant content that decreases the information load of the users (Jacoby, Speller, and Berning 1974; Malhotra 1982). (2) *Interaction-based user effort* refers to the process by which the informational content is generated. It captures the degree to which the user actively engages in the online information search environment to obtain information (Bates 1990). Based on this approach, the user can either delegate the process of locating the most relevant information to the website or actively perform the task himself (Ariely 2000; Hess, Fuller, and Mathew 2005). Increasing or decreasing user effort in either dimension has the potential to substantially affect the quality of the outcome of consumers' information search (Häubl 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 user effort reduction has emphasized its beneficial effects on the perceived quality of a decision aid as well as on system evaluation and acceptance (Bechwati and Xia 2003; Gretzel and Fesenmaier 2006; Todd and Benbasat 2000). However, an aspect which has received relatively little attention—and which is particularly relevant for content-based websites—is how different information offer approaches can affect the amount of consumer *content learning*. 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, Sarkar, and Sriskandarajah 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, Munoz-Leiva, and Luque 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 user effort reduction can help improve consumer content learning on content-based websites and that content learning subsequently forms a key driver of consumer website evaluation and revisit intention. 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 and Benbasat 2007b; Todd and Benbasat 1987). In addition, based on goal setting theory, 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: how do the dimensions of user effort (information and interaction-based) influence website evaluation and revisit intention of consumers and to what extent can these effects be attributed to the role of content learning? To study these research questions, we conducted a laboratory experiment using a health information website. Also, we examined how different ways of user effort reduction in a content-based website can have diverse effects on content learning, and in turn on website revisit intention and evaluation of the website. We showed that effort reduction is not necessarily beneficial. More specifically, on one hand, we found that decreasing information-based user effort is favorable in terms of website evaluation and continuance intention (fully mediated by the increased content learning). On the other hand, we found that decreasing interaction-based user effort is not beneficial and leads to inferior content learning (and behavioral outcomes).

The current study contributes to marketing and IS literature in several ways. Prior research has examined the relationship between user effort and system evaluation (Bechwati and Xia 2003; Gretzel and Fesenmaier 2006; Todd and Benbasat 2000). However, this is the first paper to examine the role of content learning in explaining the effectiveness of information communication in content-based websites. In addition, we propose a decomposition of user effort into two distinct dimensions, namely information and interaction-based user effort. These dimensions are respectively related to the outcome and the process of information gathering. Based on the proposed distinction, we show that lower user effort is not always beneficial proposing that the foundation for this effect is linked to the concept of content learning. Finally, we generally expand the literature related to the important area of content-based websites (Agarwal et al. 2010; Gummerus et al. 2004; Mithas et al. 2006-7; Mittal and Sawhney 2001; Song and Zahedi 2007).

The remainder of this paper is organized as follows. First, we introduce the distinction of content-based websites and their business model and review relevant theories regarding user learning. We then develop a set of hypotheses pertaining to how we expect different user effort types and levels to affect content learning outcomes, as well as the 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 study. The paper concludes with a general discussion of the findings, theoretical and managerial implications, as well as limitations and future research.

2.2 Theoretical Background

2.2.1 Content Based Websites

Depending on the scope and purpose of a website, websites can be considered as either transactional or informational (Huizingh 2000; Mithas et al. 2006-7; Quelch and Klein 1996; van Nierop et al. 2011). All websites contain a certain extent of informational content. Transactional websites avail as online purchase platforms and use this informational content as a means of persuading the visitors to purchase their offerings. In informational websites, the enclosed information is the main value component of their business and the main purpose of visit. In the first case, the information retrieved serves as a facilitator for a future purchase of the respective end product whereas in the latter case, the information acquired actually constitutes the end product (i.e. news or health information websites). Alternatively, different terms have been used to describe these websites, such as electronic information products and services (Mittal and Sawhney 2001), infomediaries (Song and Zahedi 2007), content-based (Gummerus et al. 2004) or information-oriented websites (Mithas et al. 2006-7). For the purpose of this research, we define a content-based website as an online provider with the business purpose of providing information to its visitors. Although these content based websites have gained substantial popularity (Lopes and Galetta 2006; Song and Zahedi 2007) most of the studies in the field of information systems and e-commerce focus on transactional websites.

The business and revenue model of content-based websites differs than the traditional model of e-commerce websites in that it is based on increasing usage among users and ensuring their repeated use of the website, since their revenues heavily rely on advertisement fees (Gummerus et al 2003; Liu, Sarkar, and Sriskandarajah 2010; Mittal and Sawhney 2001; Zahedi and Song 2008). The fee for advertising space is based on the amount of user traffic and enhanced reputation. The number of these users and their frequency of use are the main assets for an efficient business and revenue model. Therefore, it is in their best interest to create a large pool of loyal customers. Finally, since the actual informational content of these websites is the main value component, it is essential to examine how the accessed content is assessed by the users.

2.2.2 Information Personalization and User Effort

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, Lai, and Ku 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 marketing literature, studies on personalization are mainly related to personal interactions as an integral part of the service process (Suprenant and Solomon 1987). 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). Personalized recommendations 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; Häubl and Trifts 2000). Another stream of research aims at identifying the conditions under which personalization is more effective. Tam and Ho (2006) developed a model that posits that personalization effectiveness is influenced 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 and showed that a consumer's need for cognition plays a role in the effectiveness of information personalization. Further, prior studies also looked at when to personalize as well as how much (Ho, Bodoff, and Tam 2011; Liu, Sarkar, and Sriskandarajah 2010). The main trait of personalized decision aids designed to assist consumers in an online information search is to decrease the required consumer effort (time spent and cognitive elaboration) (Häubl and Trifts 2000; Todd and Benbasat 1994). In this paper we focus on this effort reduction through information personalization approaches within a content-based online environment.

The main objective of consumers is to jointly maximize the accuracy of their decisions and minimize their required effort in order to achieve that level of decision quality (Bechwati and Xia 2003; Johnson and Payne 1985). Inherently, according to the principle of least effort, effort is perceived as a form of cost and therefore individuals attempt to minimize it (Liang, Lai, and Ku 2007; Zipf 1949). However, by minimizing the effort in a task, users jeopardize the quality of their decisions. This contradiction in the objectives results in trade-offs needed to be made (Todd and Benbasat 1999). Respectively, in the case of content-based websites, the overall effectiveness of the website's use depends on the user's accuracy (locating the most relevant information). Therefore, since higher accuracy implies more effort from the user, the trade-off between accuracy and effort is relevant and consequential for the overall user experience and outcome. The size and direction of these trade-offs depends on the importance weight consumers assign in these two goals.

The effectiveness of a content-based website design in terms of supporting online information gathering is very important to its users. The completion of an online search 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. In order to help users deal with this trade-off, online companies introduced online decision aids in order to reduce the effort required by users and improve their experience. As a way to reduce this exerted effort, websites can provide their users with more customized content and services by using information regarding their needs and tastes (Liang, Lai, and Ku 2007). The aim of these decision aids is to assist consumers in finding the most relevant information. Previous research on online decision making showed the beneficial impact of these decision aids on both reducing the users' cognitive effort (in terms of time spent and cognitive elaboration) and improving the quality of their decisions (Häubl and Trifts 2000; Todd and Benbasat 1994; Todd and Benbasat 1999). However, some studies suggested positive effects of effort on quality perception and evaluation of a process. The effort heuristic posited that high effort in a task may result in higher valuation of a task's outcome (Cardozo 1965; Kruger et al. 2004). In addition, higher user effort may be a signal of increased decision quality and as a result, lead to more positively evaluation of the website (Bechwati and Xia 2003; Gretzel and Fesenmaier 2006; Todd and Benbasat 2000).

2.2.3 Sources of User Effort

Consumers face various types of cost, such as for example the physical, cognitive, or financial cost. Respectively, effort can take different forms. In this research, our focus is on the cognitive dimension of effort. Regarding cognitive effort, many studies treated the construct in a one-dimensional and rather subjective manner (Bechwati and Xia 2003; Hong, Thong, and Tam 2004; Wang and Benbasat 2009). Based on information load theory, user effort can be increased by increasing the size of the informational stimuli (Malhotra 1982). Moreover, user effort increases with higher involvement of users in the process (Hess, Fuller, and Mathew 2005). This involvement may derive from intrinsic sources (due to personal interest) or by situational sources (such as the environmental stimuli) (Celci and Olson 1988). A more active interaction may increase the effort required for accessing the information. From an online provider perspective, the situational form of involvement is expected to be influenced by different formats of information gathering. Respectively, the dimensions of content and interaction-based user effort can be operationalized as follows. *Information-*

based user effort refers to the degree to which customers are provided with more condensed and relevant information on the basis of their own individual needs. *Interaction-based user effort* refers to the process by which the informational outcome is generated. This second dimension captures the degree to which the consumer interactively engages with the online content-based environment to obtain the desired content (Bates 1990). We explain and illustrate these two dimensions in Figure 1.

Information-Based User Effort. Information-based user effort is related to the informational outcome of a user's visit in a website. Due to the vast amount of information available on the web, locating the most relevant information is often a difficult task for users. As a result, the information overload may hinder the effectiveness of the search (Malhotra 1982). An expected way to assist users to overcome this problem is by providing information more focused around the most related and necessary information. The degree of information-based user effort can vary depending on the final outcome. We speak of *focused information*, when the search results provide concentrated and relevant information content (measured in size of contained data) and require lower effort from users. Based on the information task, the focused content 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, Speller, and Berning 1974; Liang, Lai, and Ku 2007). On the other hand, *extensive information* exists when the consumer accesses a greater amount of information, which requires higher effort from users to identify the most relevant information compared to more focused information.

Interaction-Based User Effort. Another important aspect of the way information is offered in a content-based website deals with how the users interact with the system in order to access the informational outcome. This dimension captures the degree to which users are actively involved in the process of information acquisition (Hess, Fuller, and Mathew 2005). The level of interaction-based user effort depends on who is responsible to perform the informational task. A user can either delegate the task of collecting and organizing information services to the content-based website or can maintain the control of the information collection. The degree of interaction is based on the degree of user effort (passive versus active) as well as the control of information flow throughout the process (system driven versus user driven). Based on this assumption, we distinguish two levels of interaction-based user effort (low versus high). A user can be either passive or may need to be active in the interaction with the content-based website. 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.

Passive interaction exists when a content-based website offers the informational content without much involvement of the users. In this case, the website takes all control in finding and providing the appropriate information to customers (Khalifa and Lam 2002; Bates 1990). The user effort involved in this passive interaction condition is low. *Active 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 *interaction-based user effort* involved is considered relatively high.

Figure 2.1. Classification of User Effort on Content Based Websites

		Information-Based User Effort	
		High (Extensive Information)	Low (Focused Information)
Interaction-Based User Effort	High (Active Process)	Active Interaction / Extensive Information	Active Interaction / Focused Information
	Low (Passive Process)	Passive Interaction / Extensive Information	Passive Interaction / Focused Information

2.2.4 The Role of Learning

The role of learning has been highlighted in many aspects of human behavior. Cognitive psychologists suggested 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). The process of learning is stimulated by the encountered information. As a result, the cognitive absorption of individuals directly influences their response to the environmental stimuli and operates as a substantive bridge between the accessed information and their further behavior (Shuell 1986, Vandenbosch and Higgins 1996). 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). Research on cognitive learning pertains that cognitive absorption depends not only on the amount and nature of the content an individual receives (i.e. cognitive load theory, Malhotra 1982) but also on the learning approach the individuals use. These different approaches are related to learning by doing (goal directed problem solving) versus learning by knowing, or active versus passive learning (Bostrom et al. 1990, Shuell 1986).

We consider educational institutions as a crucial field of application of knowledge transfer and learning. As a result, our expectations are also linked to research done in purely learning environments (e.g. universities). In such environments, the cognitive performance of students can be a strong indicator of the effectiveness of an educational institution. A way to increase students' cognitive performance is to adapt the learning process to their individual needs and that leads to greater student motivation and engagement (Cordova and Lepper 1996). There is also evidence that increasing learners' control over the learning process increases their effectiveness in terms of learning outcomes and leads to greater student attitude and improvement in cognitive development (Bonwell and Eison 1991, Khalifa and Lam 2002). In online learning environments, learners' performance in terms of task achievement and memory-based recall has been linked to an e-learning program's effectiveness (Arbaugh and Benbunan-Fich 2007, Piccoli et al. 2001, Wan et al. 2008).

In decision-making literature, the concept of learning has been used in various formats and contexts: objective and subjective knowledge (Park et al. 1994), understanding (Jiang and Benbasat 2007b), cognitive learning (Dhaliwal and Benbasat 1996, Suh and Lee 2005), information retrieval (Benbasat and Todd 1996) or recall (Watson and Driver 1983). Previous studies focused on the acquisition of user skills (website knowledge) rather than content learning (Johnson et al. 2003, Murray and Haubl 2011). While process oriented learning relates to the efficacy of website use, content learning relates to the declarative level of knowledge formation that the user succeeds (Mittal and Sawhney 2001, Smith 1990). When visiting a content-based website, users wish to learn something new (learning goal) or to find information to facilitate their decisions (decision making goal). In both cases, the main goal is to access the most relevant information. Therefore, the learning outcome of an information task reflects the achievement of users' goals (Browne et al. 2007, Liu et al. 2010, Mithas et al. 2007). Goal achievement is crucial for users since a successful visit leads to higher satisfaction levels (Locke and Latham 1990).

Learning refers to any process that changes users' cognitive behavior as a result of improved information processing (Vandenbosch and Higgins 1996). Recent research showed that different types of presentation formats have a substantial effect on the amount of product learning (Jiang and Benbasat 2007a, Suh and Lee 2005). Decision aids may have a twofold effect on learning since they improve the elaboration of the decision but may also lead to some symptoms of cognitive idleness (Tan et al. 2010). To date, there is limited empirical research about what users learn from their use of websites or what the effects of learning are. In this study, we examine the effect of content learning in relation to various levels of information versus interaction-based user effort in the context of content-based websites.

2.3. Conceptual Model and Hypotheses Development

In this section we discuss our proposed conceptual model and develop the hypotheses. We disentangle the two dimensions of user effort in order to better understand the effects of effort reduction on content learning as well as on the evaluation and revisit intention of the website.

2.3.1. Information-Based User Effort and Content Learning

In online environments, information overload is closely related to the increasing volume and diversity of the available information and becomes even more important in the case of content-based websites where the information itself becomes the focal point of user-firm relationship. Although the point where individuals experience information overload is subjective and depends on various factors (e.g. familiarity), reducing the amount of information presented to users can facilitate their understanding of the information and avoid the feeling of confusion that high information load may infer (Malhotra 1982). Cognitive load theory posits that facilitation of learning can be achieved by directing cognitive resources toward processes that are relevant to learning rather than mentally integrating large amounts of information (Sweller 1988).

Users have finite processing capacity to absorb information. If they are provided with "too much" information that might exceed their processing limits, information overload might occur, leading them to poorer decision making and dysfunctional performance (Jacoby 1974). Users may become disorientated and eager to skip important information when the amount of offered information is closer to exceeding their cognitive capacity (Huang 2003, Jiang and Benbasat 2007b). As a result, a task that requires excessive cognitive resources may be less efficient and result in a state of confusion and lack of elaboration (Tan et al. 2010). Therefore, decision aids that reduce the effort by offering more condensed content are expected to facilitate information absorption. Therefore,

- **Hypothesis 1a.** *Reducing the information-based user effort increases content learning.*

Reducing the amount of content presented to users facilitates them in processing the information due to the decrease in the encountered cognitive load. Thus, in an indirect way, the effectiveness of a content-based website is increased when information can be presented in a more focused manner (Cline and Haynes 2001). The concept of learning has been used to develop an indication of the effectiveness of information transmission and communication by different system interfaces (Large et al. 1994). When visiting a content-based website, the learning outcome of the visit can reflect the achievement of the user's informational goal and can be a driver of the evaluation of the experience (Browne et al. 2007). At the end of the 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 in relation to users' behavioral and attitudinal outcomes (DeLone and McLean 2003, Nelson et al 2005, Palmer 2002). The amount of content learning signifies the degree of effectiveness and perceived usefulness of a website and is related to the users' performance during a website visit and therefore can affect their attitude towards it (Dabholkar and Bagozzi 2002). Mittal and Sawhney (2001) suggested that content learning in a website can positively influence the evaluation of the visited website. 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 improves users' attitudes towards it (Jiang and Benbasat 2007a).

Inherently, when user effort required in a task is reduced, that signifies a cost reduction. In such a case, users positively evaluate the content-based website. However, the final assessment of a website's evaluation depends on both the goals of accuracy maximization and effort minimization (Johnson and Payne 1985, Todd and Benbasat 1999). If the benefits which are related to the cognitive absorption of the information are low, despite the reduction of the cost, the overall assessment is disputable. If content learning is low, users may feel that the website does not fulfill its expectations and therefore the effects of information-based user effort reduction on the evaluation of the website are not influential. Learning has been suggested both in cognitive psychology (Shuell 1986, Vandenbosch and Higgins 1996) as well as in IS literature (Dhaliwal and Benbasat 1996, Suh and Lee 2005) as the bridge between the stimuli and the behavioral response of individuals. Therefore,

- **Hypothesis 1b.** *Content learning mediates the positive effect of information-based user effort reduction on website evaluation.*

Moreover, reducing information-based users' effort by limiting the informational outcome to only the core part can make them more satisfied with the website, which in turn would lead to a higher intention to revisit the website (Srinivasan et al. 2002). An essential driver of the business model of content-based websites is the formation of a returning user base through the fulfillment of their needs (Gummerus et al. 2004). System continuance intention has received broad attention in the literature (Bhattercherjee 2001, Limayem et al. 2007). In online environments, the learning experience from using a website can become a key source of competitive advantage for online firms regarding consumer retention and word of mouth (Mittal and Sawhney 2001, Wang 2003). Also, research applied in educational institutions highlighted the importance of knowledge formation in the effectiveness of a learning technique (Umbach 2000) as well as in student commitment and retention to the educational institution (Aitken 1982, Hartman and Schmidt 1995).

Since in the case of content-based websites, the main goal of users is to access the right information, we expect that higher content learning will lead to a higher intention to revisit the website. However, though users would be more satisfied when they minimize their effort required, the overall intention to reuse the system depends on the actual benefits they experience. This implies that though focused information might reduce their effort, their learning goal remains the main benefit and therefore is highly influential on users' decision for future use of the website. Therefore,

- **Hypothesis 1c.** *Content learning mediates the positive effect of information-based user effort reduction on intention to revisit the website.*

2.3.2 Interaction-Based User Effort and Content Learning

An additional dimension of user effort relates to the level of interaction between users and websites and regards interaction-based user effort. Some information-based websites require users to be more active in locating the content they need whereas some other websites attempt to minimize user effort by taking full responsibility of the process of providing the information. In this case, in contrast to information-based user effort, we expect that reducing the interaction-based user effort operates under a different mechanism and decreases the amount of content learning of the users.

One of the cognitive learning approaches with the longest tradition is the distinction between active and passive learning (Bostrom et al. 1990, Shuell 1986). The literature on education concludes that active learning, where the control of the learning process is given to the student, can lead to higher learning outcomes and evaluation of the content and structure of the learning process compared to distributed passive learning processes both in online and offline environments (Bonwell and Eison 1991, Khalifa and Lam 2002). Giving control to learners to draw their own conclusions is beneficial since information retrieved with high cognitive effort is more likely to be retrieved from memory compared to information that is processed with less effort, even if that increases their cognitive effort (Sawyer and Howard 1991, Tyler et al. 1979). In this line of research, evidence was found regarding increased comprehension and duration of retention of the acquired information of the content of a website influenced by higher levels of involvement and control (Ariely 2000, Lustria 2007). Regarding online decision making, Users show greater comprehension of the information when they are more involved in the process (Celci and Olson 1988, Hess et al 2005). Based on the "generation effect" when individuals self-generate the information, memory performance is better than when the information is explicitly given to them (Kardes 1988, Lichtenstein and Srull 1985). Finally, more interactive presentation of information is more engaging and can increase the amount of understanding (Jiang and Benbasat 2007b, Suh and Lee 2005). As a result, by delegating all the control for the information gathering process to the website, users are less involved and more passive and are consequently expected to show inferior learning performance. Therefore,

- **Hypothesis 2a.** *Reducing the interaction-based user effort decreases content learning.*

Reducing the effort based on the interaction between the user and the content-based system may implicitly appear appealing to users but may also decrease the understanding the information due to lack of control and involvement. Especially in the case of content-based websites, learning is substantial since it captures the level of users' goal achievement. Also, the managerial importance of content learning can be highlighted due to the business model of these websites (Mittal and Sawhney 2001, Gummerus et al 2003). Content-based websites are interested in attracting users and ensuring their repeated use of the website, since their revenues heavily rely on charged fees for placed advertisements (Liu et al 2010, Zahedi and Song 2008). Therefore, they aim at creating customers who highly evaluate the website and repeatedly return to the website.

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 a stimulus compared to less effortful explicit conclusions provided

(Botti and Iyengar 2004). Many empirical studies in consumer information processing showed a positive correlation between task involvement and task attitude (Hess et al. 2005). In addition, in online learning environments, a high level of active interaction with the system is related to higher satisfaction and evaluation of the online medium (Arbaugh and Benbunan-Fich 2007). The reason is that when users take control of the learning experience their self-efficacy increases. Therefore, though by delegating control to the system, user effort regarding the interaction is reduced, the overall valuation is expected to depend on the amount of content learning. Users that delegate control to the system feel less involved when a website takes over all the interaction and are likely to value the experience less (Jiang and Benbasat 2005, Jiang and Benbasat 2007a). In addition, based on the theory of psychological reactance, users react and evaluate more negatively a system that restricts their freedom of choice, even if objectively it may lead them to improved decision quality (Brehm 1966, Murray and Haubl 2011). The reduced interaction-based user effort may have a positive direct effect on website evaluation but its effect on content learning is highly negative which in turn decreases website evaluation and intention to revisit. Therefore,

- **Hypothesis 2b.** *Content learning mediates the negative effect of interaction-based user effort reduction on website evaluation.*

An essential driver of long term success for content-based websites is the formation of a returning user base (Zahedi and Song 2008). System continuance intention has received broad attention in the literature (Bhattercherjee 2001, Gummerus et al 2004, Limayem et al. 2007). The perceived control of users is positively linked to their intention to return to a website (Koufaris 2002). The reason is that increasing users' active involvement in the interaction with a website by leaving the control of the experience to them can boost their self-efficacy and lead to the creation of a stronger bond with the website (Ariely 2000, Jiang and Benbasat 2007a). In addition, learning can serve as a strong mediator of further behavior (Suh and Lee 2005). Therefore it is expected that even though passive interaction offers a quicker and less effortful path (which is expected to have a positive effect), there is a counterbalanced effect of users' decreased learning. Therefore,

- **Hypothesis 2c.** *Content learning mediates the negative effect of interaction-based user effort reduction on intention to revisit the website.*

2.4. Methodology

To test the effects of information provision across different levels and sources of user effort reduction, we conducted two experimental studies (a pretest and the main experiment) where participants were asked to visit a content-based website to acquire the necessary information based on a given scenario. In the pretest, we first test the effects of content learning regarding users' behavioral outcomes and further investigate whether information personalization leads to favorable behavioral outcomes and is mediated by the amount of content learning. In the main experiment, we distinguish between information and interaction-based user effort, 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 information-based (high versus low) and interaction-based (high versus low) user effort.

We used a health information website because of its information rich content and since the digital transformation of healthcare management places the industry in the limelight of interest from an IS perspective (Agarwal et al 2010; Song and Zahedi 2007; Zahedi and Song 2008). The vital role of online health information delivery has been well documented. In a recent survey of 2065 adults in the U.S., PEW Internet (www.pewinternet.org) reports that 80% look for health information online in a rather systematic way (Fox 2011). We used the existing medical website www.webmd.com for two reasons. First, it is one of the most visited health websites worldwide (according to www.alexa.com) and also used in previous field studies (Song and Zahedi 2007). Therefore, we could control for unfavorable behavioral outcomes of the users due to bad quality of content and lack of trust in the website. Second, the website offers a range of health-related information in a variety of ways that vary in terms of information or interaction-based user effort, thus providing a natural experimental setting for us.

2.5. Pretest: The Effect of Personalized vs. Generic Information

The purpose of the pretest is to explore the effect of providing personalized information compared to providing generic information and also to examine the role of content learning within this context. With this pretest, we wanted to highlight the role of content learning within the context of information communication in a content-based website and also to confirm that effort reduction holds compared to a non-personalized information condition.

Pretest Procedure. 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 participants received personalized and condensed information from the website. In the generic information condition participants received a generic list with the most popular health topics in the website, where the health conditions in the scenario were picked from. 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 the health condition described in a scenario. We guaranteed that participants were not able to visit any other website during the experiment (due to some restriction in the browsers). 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.

Pretest Descriptives. 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 either 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. To check whether the personalized condition indeed reduces the required effort of participants, we compared the time needed to assess the information needed (Bettman, Johnson, and Payne 1990). 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) ($t=84.96$, $p<0.01$).

Pretest Measurement Model. The items used in order to measure our constructs are similar to the main experiment (see Table 2.5). For our analysis, we used partial least squares (PLS) with SmartPLS (Ringle, Wende, and Will 2005). PLS was chosen due to the high flexibility and statistical power regarding theory building (Hair, Ringle, and Sarstedt 2011). First, we constructed the first order latent variables and then related these factors to the second order factor of website evaluation (Abdinnour-Helm, Chaparro, and Farmer 2005)[3]. 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. 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, Straub, and Boudreau 2000). Moreover, all AVE values were above the recommended value of 0.5. 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 (see Table 2.2). 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.

Pretest Results. We tested whether content learning has a mediating role between the information communication condition and the behavioral outcomes (three-step procedure proposed by Baron and Kenny 1986). An overview of the mediation test results is presented in Table 2.3. 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 ($\beta=0.43$, $t=10.98$, $p<0.01$). Effort reduction by offering personalized information to respondents leads to higher content learning ($\beta=0.27$, $t=6.87$, $p<0.01$). The direct effects of information communication condition on website evaluation ($\beta=0.19$, $t=4.23$, $p<0.01$) as well as on the revisit intention ($\beta=0.20$, $t=4.81$, $p<0.01$) are positive and significant. When controlling for the amount of content learning, these effects disappear, which suggests full mediation.

[3] 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 (Bailey and Pearson 1983; Doll and Torkzadeh 1988).

Table 2.1. Assessing the Hierarchical Model of Website Evaluation in Pretest				
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[4]		
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 2.2. 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

Table 2.3. Results for Mediation Effect								
			Coefficient in Regressions				**Sobel Test for indirect effect**	**Mediation Result**
			Step 1	**Step 2**	**Step 3**			
IV	**M**	**DV**	**IV→DV**	**IV→M**	**IV+M→DV**			
					IV	**M**		
Personalized Information	CL	WE	0.19**	0.27**	0.07	0.43**	z=5.14*	Full
	CL	IR	0.20**	0.27**	0.06	0.43**	z=4.46*	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.
Note 3: CL: Content learning, IR: Intention to revisit, WE: Website Evaluation

[4] Similarly to the end-user satisfaction scale, the variation explained in the timeliness factor was low (Cronbach's α<0.5), which undermined the overall validity of the second order factor of website evaluation (AVE<0.5). We decided to drop this factor for further analysis based on Abdinnour-Helm et al. (2005).

2.6. Main Experiment: The Conflicting Effect of Information versus Interaction Based User Effort

In the main experiment, we distinguish between information-based and interaction-based user effort reduction, and examine the effects of both dimensions on behavioral outcomes of the users mediated by content learning. We demonstrate that decreasing the effort does not have the same effect across the two dimensions. Participants visited the same website (www.webmd.com) and followed a similar procedure as in the pretest.

2.6.1. Study Design and Procedure

Study Design. 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. We disentangled information-based versus interaction-based user effort across the different experimental conditions. We demonstrate that decreasing the effort does not have the same effect across the two dimensions. The detailed manipulations for the two experimental conditions can be found in Table 2.4.

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 an experimental condition: active vs. passive interaction (high vs. low user effort respectively) and extensive vs. focused information (high vs. low user effort respectively). Participants were asked to visit the website to acquire the information they needed to identify the health condition described in the scenario, as well as its possible treatments. We ensured that participants were not able to visit any other website during the experimental task. 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 2.2.

Measurement of Constructs. We summarized the items used to measure the proposed constructs in the conceptual model in Table 2.5.

User Effort Conditions. User effort conditions were measured by two binary variables based on the respective manipulations of the two dimensions.

Content Learning. Recall from memory is found to be a relatively good proxy of the objective assessment of knowledge (Kanwar, Grund, and Olson 1990; Khalifa and Lam 2002; Suh and Lee 2005). Recall signifies the effectiveness of information provision through different ways, when there is a specific search target to be found. In the case of content based websites, the target was specific and no browsing is involved in this process (Hong, Thong, and Tam 2004). Thus, we measured content learning based on a recall accuracy test. More specifically, we measured the percentage of questions correctly answered[5].

Table 2.4. Manipulations of Independent Variables
Information-Based User Effort: 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 information condition (high user effort)*, the informational outcome was an approximately 1000 words document related to the health condition. In the *focused information condition (low user effort)*, the informational outcome was an approximately 200 words document with condensed information concerning the health issue.
Interaction Based User Effort: 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 interaction condition (high user effort)*, participants were asked to take all control and interact with the website and evaluate on their own the outcomes before choosing the most appropriate information. In the *passive interaction condition (low user effort)*, participants delegated the process of finding the information to the website. After requesting an answer from an expert from the website, users, without having to actively search, received a document with information about the health condition that best fitted 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.

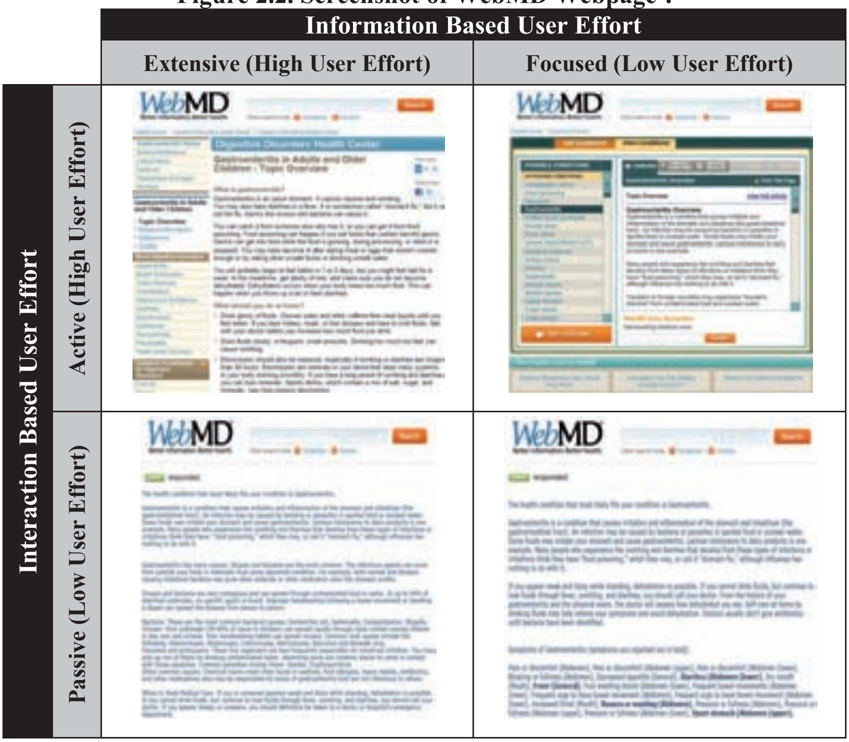
Website Evaluation. Many studies measured the effectiveness of an information system in terms of quality aspects (Bailey and Pearson 1983; DeLone and McLean 1992; Doll and Torkzadeh 1988). The level of quality that a website offers can capture users' satisfaction. DeLone and McLean (1992) measured information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

[5] The questions could be correctly answered regardless the user effort condition.

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, Chaparro, and Farmer 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 (see Table 2.5 for a more detailed illustration of the measurement items used). 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.

Figure 2.2. Screenshot of WebMD Webpage[6].



2.6.2. Data Analysis and Findings

A total sample of 249 students participated in the study. They were randomly assigned

[6] The screenshots are used to offer an impression of the used conditions.

to four different versions of information provision based on information-based (extensive versus focused) and interaction-based user effort (active versus passive). The participants' characteristics can be found in Table 2.6.

Manipulation Check. The two dimensions of user effort used 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, we registered the time spent searching and processing the information as a proxy for user effort (Bettman, Johnson, and Payne 1990). The results showed that the average time needed in the extensive information (high user effort) condition (351 seconds) was significantly higher than that in the focused information (low user effort) condition (291 seconds) ($t=5.35$, $p<0.05$). Thus, the manipulation of information-based user effort was successful. Users that are more involved with a system tend to spend more time using a system. Therefore, user effort can be evaluated through decision-making time (Hess, Fuller, and Mathew 2005). Similarly, for interaction-based user effort, the results showed that the average time needed (in seconds) to find and process the information in the active interaction (high user effort) condition (547 seconds) was significantly higher than that in the passive interaction (low user effort) condition (227 seconds) ($t=180.31$, $p<0.01$), indicating a successful manipulation.

Table 2.5. Measurement and Items		
User Effort Conditions: We used a binary coding for user effort conditions. We used the variables Information -Based User Effort and Interaction-Based User Effort for the two dimensions. The value of 1 corresponds to low user effort needed in the respective dimension. More specifically, Information-Based User Effort has the value of 1 for the focused information, and Interaction-Based User Effort has the value of 1 for the passive interaction.		
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**
Content	C1	The information I found on the website is precise.
	C2	The information I found on the website is of high quality.
	C3	The information I found on the website covers my needs.
	C4	The information I found on the website is complete.
Accuracy	A1	The information I found on the website is reliable.
	A2	The information I found on the website is accurate.
Format	F1	The information I found on the website is clear.
	F2	The website is well organized.
	F3	The website is well formatted.

Ease of Use	E1	The website is easy / complex to use.
	E2	The website gives easy access to information.
Timeliness	T1	The website gives quick access to information.
	T2	The information on the website is up-to-date.
Intention to Revisit: If you had a future need for health related information, how likely would you consider visiting www.webmd.com?		

Measurement Model. We tested the hypotheses using partial least squares (PLS) with SmartPLS (Ringle, Wende, and Will 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, Ringle, and Sarstedt 2011). First, we constructed the first order latent variables and then related these factors to the second order factor of website evaluation (Abdinnour-Helm, Chaparro, and Farmer 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, Chaparro, and Farmer (2005).

Table 2.6. Participants Characteristics		
Number of Participants	249	
Age	21.4 (2.6)*	
Gender	Male	52.6%
	Female	47.4%
Education	Bachelor	64.7%
	Master	30.5%
	Other	4.8%
Internet Experience (Years of Internet use)	< 6 years	59.1%
	> 6 years	41.0%
Frequency of use (Hours per week)	< 20 hours	37.3%
	>= 20 hours	62.6%
Have you ever visited the website?	No	95.6%
	Yes	4.4%
Searched for online health information before?	No	10.0%
	Yes	90.0%

* mean (standard deviation)

We summarize the results in Table 2.7 and 2.8. 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, Straub, and Boudreau 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 0.73 (Tenenhaus et al. 2005), indicating good performance of our model.

Structural Model. We measured the significance of the relationships between our independent and dependent variables (see Figure 2.3). The results showed that the model accounted for 40% of the variance regarding website evaluation and 50% of the variance for intention to revisit the website, which is moderate (Chin 1998). The results of this study provide strong support for the respective hypotheses.

First, we tested the direct effect of information-based user effort on content learning (see Figure 2.3). Focused information (low user effort) has a significant and positive effect on content learning (β=0.19, t=4.57, $p<0.05$), confirming H1a. Second, we tested the direct effect of interaction-based user effort (passive interaction) on content learning and found a significant negative effect (β=-0.37, t=10.47, $p<0.05$), confirming H2a.

We followed the three-step approach of Baron and Kenny (1986) to test the mediation effect. In the first step, we found that regarding information-based user effort, decreasing the effort needed due to more focused information 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 interaction-based user effort, 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 the information (focused) increases learning whereas the respective effect regarding the 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 holds for the dimensions of user effort. 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 information-based user effort, 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. We further conducted a Sobel test to examine whether the direct effect of information-based user effort is significantly reduced when adding the mediator (i.e. content learning) to the model (Preacher and Hayes 2004). We indeed found a significant indirect effect of information-based user effort on both website evaluation ($z = 5.14$, $p < 0.05$) and intention to revisit the website when content learning is introduced ($z = 4.46$, $p < 0.05$). Therefore, in both cases we deal with indirect only mediation (Zhao, Lynch, and Chen 2010). Therefore, H1b and H1c are supported.

Regarding interaction-based user effort, by including content learning, we found that the effect of low effort (passive) 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 more active interaction is negative which can be explained by its negative effect on content learning. The effect of interaction-based user effort 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. We further conducted a Sobel test to examine whether the direct effect of information-based user effort is significantly reduced when adding the mediator (i.e. content learning) to the model (Preacher and Hayes 2004). We indeed found a significant indirect effect of information-based user effort on both website evaluation ($z =-9.40$, $p < 0.05$) and intention to revisit the website when content learning is introduced ($z = -5.47$, $p < 0.05$). Regarding website evaluation, since the sign of the overall effect is negative, we have a case of competitive mediation (Zhao, Lynch, and Chen 2010). Regarding intention to revisit, the positive overall effect indicates a complementary mediation (Zhao, Lynch, and Chen 2010). As a result, H2b and H2c are supported. A detailed description of the mediation results can be found in Table 2.9. We summarize all hypotheses testing results in Figure 2.3 and Table 2.10.

Table 2.7. 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
A2	0.76	**0.91****	0.57	0.54
F1	0.62	0.58	**0.81****	0.48
F2	0.44	0.44	**0.81****	0.70
F3	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 2.8. 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

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). 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 user effort 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. 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 (however with the inclusion of these variables, our conclusions remain consistent).

Table 2.9. Results for Mediation Effect

			Coefficient in Regressions				Sobel Test for indirect effect	Mediation Result
			Step 1	Step 2	Step 3			
IV	M	DV	IV→DV	IV→M	IV+M→DV			
					IV	M		
Focused Information	CL	WE	0.09*	0.19**	-0.04	0.67**	z=5.14*	Full
	CL	IR	0.15**	0.19**	0.06	0.58**	z=4.46*	Full
Passive Interaction	CL	WE	-0.13**	-0.39**	0.11**	0.67**	z=-9.40*	Full
	CL	IR	-0.31**	-0.39**	-0.15**	0.58**	z=-5.47*	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 information-based user effort, Passive: Low interaction-based user effort, CL: Content learning, IR: Intention to revisit, WE: Website Evaluation

Figure 2.3. Summary of Results in Structural Model

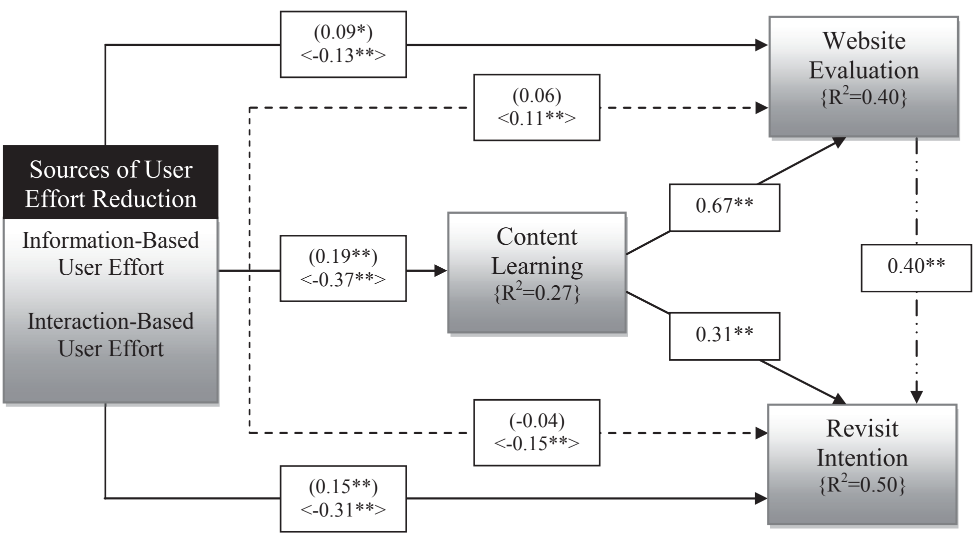


Table 2.10. Summary of Hypotheses Testing Results		
Hypotheses		Result
1a	Reducing the information-based user effort increases content learning.	Supported
1b	Content learning mediates the positive effect of information-based user effort reduction on website evaluation.	Supported
1c	Content learning mediates the positive effect of information-based user effort reduction on intention to revisit the website.	Supported
2a	Reducing the interaction-based user effort decreases content learning.	Supported
2b	Content learning mediates the negative effect of interaction-based user effort reduction on website evaluation.	Supported
2c	Content learning mediates the negative effect of interaction-based user effort reduction on intention to revisit the website.	Supported

Note 1: For effect of User Effort: (Focused vs. Extensive Content-Based User Effort), < Passive vs. Active Interaction-Based User Effort >
Note 2: ** Significant at the 0.01 level; * Significant at the 0.05 level
Note 3: ⟶ Direct effect.
- - -► Effect when Content learning is included.
-·-·► Not specifically hypothesized but path included for statistical testing.

2.7. General Discussion

2.7.1 Discussion of the Findings

In this paper, we argue that content learning captures and explains the level of effectiveness that different ways of effort reduction regarding information acquisition in a content-based website can succeed. Content learning has been largely neglected from the IS and marketing literature, especially in the case of content-based websites where the main goal of the users is to access and comprehend the informational content they offer. Mittal and Sawhney (2001) suggested that the overall learning experience can impact subsequent behavior towards a website. We propose that content learning is an integral part of the user-website interaction and that the way the information is communicated can influence the amount of content learning. The results of an experimental study underline the importance of user effort and content learning in forming several behavioral outcomes in content-based websites.

We show that the information in a content-based website can be offered in multiple ways that vary in the level of user effort they require. However, though traditionally, effort is regarded as a cost that users wish to minimize (Bechwati and Xia 2003; Johnson and Payne 1985; Todd and Benbasat 1999), effort reduction offered by content-based websites is not always beneficial. Some approaches, despite requiring higher effort from the users may have a positive effect on content learning and their effectiveness can vary depending on the source of user effort required. To explain these differences we propose that user effort should be conceptualized in terms of two dimensions based on the content of information and the interaction of users with the website. We disentangle user effort into information-based (related to the outcome) and interaction-based (related to the process). These different dimensions of user effort can have different effects on content learning. More precisely, our results suggest that while lowering the effort with respect to information increases content learning, lowering effort regarding interaction has the opposite effect. Lower information-based user effort focuses users on the core of the informational content needed and bypasses any risk of overload which harms learning (Jacoby, Speller, and Berning 1974; Malhotra 1982). Conversely, lowering the effort regarding the interaction means that users delegate all control to the website in order to minimize their effort needed and therefore they receive the information delivered in a more passive way. Whereas, in principle, such an approach seems appealing to the users, we show that this type of effort reduction may be undermined by the inferior learning performance of the users.

Content learning significantly influences the users' behavioral outcomes in a content-based website. We used website evaluation and intention to revisit the website to describe users' behavioral outcomes. The main reason is that these two factors are closely related the business and revenue model of these websites. Website evaluation has been closely linked to users' satisfaction as well as the quality of the website (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 content-based websites. The ability to retain a large pool of repeating users can guarantee the survival of these websites, which is also subject to their ability to sell advertising space (Song and Zahedi 2007). Our results supported our expectation regarding the effect of content learning on these behavioral outcomes. These effects are consistent with the goal achievement theory that argues that completion of a goal leads to greater attitude and valuation of an experience (Locke and Latham 1990).

In summary, while prior research in IS has examined the relationship between user effort and system evaluation (Bechwati and Xia 2003; Johnson and Payne 1985; Todd and Benbasat 1999), this study is the first to examine the role of content learning in explaining the effectiveness of different approaches of information communication varying in terms of user effort. The results of this study show that (1) decreasing information-based user effort has *positive* effects on users' content learning, (2) decreasing interaction-based user effort has *negative* effects on users' content learning and (3) content learning mediates the differential effects of the two dimensions of user effort on users' behavioral outcomes. More specifically, when users experience low information-based effort (more focused and relevant information), they have more favorable subsequent behaviors. These effects are fully explained by the increased content learning emerged from the reduction of information load. However, regarding user-website interaction, lowering the effort required by users has the opposite result. Though higher effort from users would lead to lower valuation of the system, active involvement can be beneficial due to increased benefit of content learning that users can achieve.

Finally, we show an interesting additional result regarding interaction-based user effort and website evaluation. Without taking into consideration the amount of content learning, the effect of high effort interaction (active 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 the overall positive effect of the interaction-based user effort can be attributed to the increased content learning. However, when we control for that effect (which captures the benefits gained), the remainder is the direct effect of effort (signifying the cost of the process), which is undesirable for users (Bettman, Johnson, and Payne 1990). More practically, when users experience equal levels of content learning, their evaluation would be higher when they have made this achievement with lower effort.

2.7.2. Theoretical Contributions

In recent years, there is an increased interest in investigating the role of user effort within the context of user-website interaction (Bechwati and Xia 2003, Liang et al. 2007). The current study contributes to this literature in a number of ways.

First, different from past research that treats user effort as a singular and subjective measure (Bechwati and Xia 2003, Hong et al 2004, Wang and Benbasat 2009), in this paper we disentangle user effort into two distinct dimensions, namely information-based and interaction-based user effort, related respectively to the outcome and the process of information gathering. This is different from prior research that mainly considers different sources of effort distinguishing between users versus system driven effort (Bechwati and Xia 2003). We show that user effort can be reduced in two ways. First, user effort is reduced by providing more dense and tailored content based on user needs and, second, by allowing users to decide on the way the informational content is accessed (capturing the way in which users interact with the website).

Second, in this study, we theoretically propose and empirically test the role of content learning in information communication and its impact on users' further behavioral outcomes. In addition, we demonstrate how content learning is influenced by different specifications of information and interaction-based user effort requirements 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 in online decision making 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 2011). However, the importance of content learning regarding the effectiveness of a system has been suggested by a few studies (Mittal and Sawhney 2001, Piccoli et al. 2001). In this paper, we propose that content learning plays a greater role in content-based websites, 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 content-based website can signify their individual performance which, in turn, can influence their attitude towards the website.

Third, this study provides a framework that illustrates a mechanism through which information communication can be improved. We argue that effort reduction is not always beneficial. Although analogous claims can be found in the literature (Cardozo 1965), in this study we propose that the basis for this underperformance can be related to the concepts of user effort types and content learning. Our findings imply that the effect of effort reduction is not equally beneficial for different types of effort. We show that while decreasing the information-based user effort is beneficial for the website, the same approach toward interaction-based effort shows counter effects. The underlying reason is that more interaction-based effort may be related to greater content learning which is a substantial driver of user response towards the website. This finding is consistent with the theory of psychological reactance (Murray and Haubl 2011), as well as 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).

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 user effort and learning 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.

2.7.3. Managerial Implications

From a managerial viewpoint, this study spotlights several crucial issues for online firms. First, in the debate on whether user effort reduction is always beneficial, we provide further evidence for the understanding of its role. Even though reducing the user effort through various ways of information communication 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 approaches. Examples of such firms can be found in online news (e.g. Wall Street Journal, MyYahoo), financial services (e.g., ABN AMRO credit card, Independer.nl) and educational institutions (e.g. Northcentral University). Therefore, a better understanding of when and how these approaches of effort reduction can have optimal results is very important for the success of these firms (Liu et al. 2010). Our study shows that achieving an effective user effort reduction is not a one dimensional endeavor. We distinguish between two discrete dimensions of user effort, showing that this distinction is of high importance and relevance for online managers since it gives a more structured view of the mechanism of information provision. Based on our results, websites can manipulate their way of communicating their content based on the amount of user effort needed regarding the information and the required interaction level of users. Taking into account the role of content learning, we show that different types of user effort may lead to different system evaluation. Online firms work hard on finding ways to assist their users and to make their navigation easier and less effortful. By introducing the two dimensions of user effort, we can explain some of the debatable findings regarding the role of effort (Bechwati and Xia 2003, Cardozo 1965, Todd and Benbasat 2000). Especially in the case of content-based websites, online managers should not focus only on making 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 full 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 hence important for online information providers to be aware of the options of information communication to increase user learning. They may consider reducing the information-based user effort but giving more control to the users to generate higher learning benefits. Also, given the heterogeneity across users (even within a given website), a one-size-fits-all approach may not be necessarily viable. Based on our user effort distinctions, websites can also offer the control of choosing the way information is offered to their users.

Second, 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 effects of different ways of user effort reduction 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 these 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 information communication. 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. We show that these indications can be 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 and easily comprehended by their 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

2.7.4. Limitations and Future Research

We discuss some limitations of this study and some avenues for future research. First, whereas we show that in content-based websites, higher user 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) approach of interacting with the website can lead to higher effectiveness if used but, also, whether users will select it when also given the option of a more passive approach (Ariely 2000). Therefore, it would be interesting to investigate what makes users choose among different information formats that differ in terms of required effort. The intention to revisit results from our studies showed that users would more likely choose low information-based effort and high interaction-based effort 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 (Ariely 2000) and the feeling of ownership over the outcome of the process. Understanding such motivational factors is vital, since in the long run they can determine consumers' desire to fully utilize more interactive 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 especially when there is a specific search target to be found (Hong et al. 2004-5, 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, using a recall test 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 information-based user effort we draw on the idea of information overload to suggest that providing extensive information 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 information-based user effort that can maximize learning and behavioral outcomes. However, in this study we focus on the positive effect of information-based effort reduction per se (compared to higher effort) 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. Also, it would be insightful to investigate whether the role of content learning holds in a transactional setting as well.

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.

2.7.5. Conclusion

In summary, the current work has investigated the effects of user effort and content learning in the context of content-based websites. Using a distinction in operationalizing user effort into information-based and interaction-based, we show that user effort is not always equally beneficial. 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 different information provision approaches that vary in terms of user effort required regarding the aforementioned behavioral outcomes. An improved understanding of how user effort 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 user effort on website evaluation and revisit intentions underline the conclusion that given the proliferation of information online, the real question for content-based websites is not whether to reduce user effort or not, but rather how to reduce it.

Μετά πόνου η μάθησις
We cannot learn without pain
Aristotle (384 - 322 BC)

Chapter 3

The Effects of Choice Set Complexity on Consumer Product Knowledge

3.1 Introduction

From a managerial standpoint, in many business practices such as financial services and online advisory services, where complex products are sold, companies are increasingly held accountable for promoting sufficient levels of product understanding to their customers. This need becomes even more imperative in e-commerce where disseminating information about the products becomes trivial due to the absence of tangibility (Suh and Lee 2005). Firms can improve consumers' product understanding by improving the knowledge of their customers through the online content that they offer. Traditionally, strategies to promote consumer product knowledge have focused on providing more and richer product information to consumers. However, increasing the amount of information may lead to higher cognitive load, which in turn is detrimental regarding the cognitive outcomes of the consumers (Jacoby 1984). In addition, rich and interactive product information presentations may be more engaging and enhance consumer learning (Jiang and Benbasat 2007; Suh and Lee 2005), but remain relatively costly and require a certain processing capabilities to be efficient.

In the previous chapter, we investigated the role of information absorption in content-based websites. In this chapter we aim at investigating the role of information absorption in a transactional setting. More specifically, in this study we propose that differences in the composition of the product choice sets that are offered to consumers can also influence consumer product knowledge. Many decisions consumers face on a regular basis entail a certain degree of complexity and uncertainty. The degree of choice difficulty occurs due to the need of consumers to confront the conflict between costs and benefits of the offered products (Thompson, Hamilton, and Petrova 2009). More specifically, we investigate the effect of choice set complexity and how it distinctively impacts two discrete forms of knowledge; objective and subjective consumer knowledge (Brucks 1985; Carlson et al 2009; Moorman et al 2004; Park, Mothersbaugh, and Feick 1994). This distinction is based on the assumption and evidence that what consumers actually know does not necessarily comply with what they think they know (Alba and Hutchinson 2000; Bearden, Hardesty, and Rose 2001; Carlson et al 2009; Moorman et al 2004). Accordingly, we propose that greater choice set complexity increases objective consumer knowledge because complex choice sets require greater cognitive elaboration on the alternatives. When consumers face complex choice sets they follow a more deliberate approach in order to make an informed choice (Klein and Yadav 1989; Mehta, Hoegg, and Chakravarti 2011; Sela, Berger, and Liu 2009; Shugan 1980). Conversely, greater complexity also is likely to lead to decreased consumer choice confidence (Bearden, Hardesty, and Rose 2001; Brucks 1985; Carlson et al 2009) and therefore we expect that it lowers subjective product knowledge. Consumers who face a more difficult choice are more likely to feel uncertain about their processing ability of the information (Gill, Swann, and Silvera 1998; Kelley and Lindsay 1993).

We test our hypotheses using clickstream data from a financial product comparison website combined with brief online surveys, as well as data from a controlled experimental lab environment in the consumer electronics product category. We show that in a natural setting, choice set complexity can explain a considerable amount of variation in consumer knowledge. The second study is set in a controlled experimental environment where we confirm that our expectations hold when we control for external factors that might influence consumer behavior.

This study seeks to extend the research on the antecedents of consumer product knowledge. First, we show that choice set complexity can influence consumer product knowledge. However, whereas higher complexity is not necessarily a disadvantageous trait of choice sets since it can increase objective product knowledge, we also show that its effect on consumers' subjective knowledge assessment is detrimental. This contradiction offers additional support on the current assumption that the two components of consumer knowledge have different antecedents. Also, we validate that the effect of choice set complexity on consumer product knowledge is managerially meaningful in providing evidence for its influence on consumer conversion and willingness to pay for the chosen alternative. Finally, we provide a more generalizable framework by finding support of our expected relationships in two distinct product categories and across distinct methods of data collection.

3.2 Theoretical Framework

3.2.1 Consumer Product Knowledge

In general, the importance of knowledge has been emphasized across various parts of human behavior. A psychological approach suggested that consumer knowledge relies on the cognitive changes due to the interaction between information cognitive processing and environmental stimuli (Vandenbosch and Higgins 1996). Studies in social psychology showed that knowledge moderates the relationship between attitudes and actual behavior across various applied learning approaches (i.e. behaviorist, cognitivist or constructivist approach) (Bargh and Ferguson 2000; Kettanurak, Ramamurthy, and Haseman 2001). The degree of product knowledge can stimulate consumers' responses to the informational stimuli and further influence their behavior (Shuell 1986; Vandenbosch and Higgins 1996).

Past research regarding consumer knowledge has suggested two discrete forms of knowledge; objective and subjective knowledge (Brucks 1985; Carlson et al 2009; Moorman et al 2004; Park, Mothersbaugh, and Feick 1994). Objective knowledge captures what consumers actually know and is based on the accuracy of their recall measures unaffected by any self-presentation and response biases. Subjective knowledge is related to what consumers believe they know and is highly linked to consumers' confidence on their beliefs (Alba and Hutchinson 2000; Bearden, Hardesty, and Rose 2001; Carlson et al 2009; Tsai and McGill 2011). Although in principle, these two components of consumer knowledge are expected to be closely linked, substantial deviation has been reported in the past, ranging from strong positive correlation to weak or no correlation at all (Carlson et al 2009; Moorman et al 2004; Park, Mothersbaugh, and Feick 1994). The reason is that the underlying mechanisms through which self-assessed knowledge and objective knowledge affect consumer behavior are different (Bettman and Park 1980; Brucks 1985; Park and Lessig 1981). In addition, objective and subjective knowledge have different antecedents (Park, Mothersbaugh, and Feick 1994). Due to social desirability biases, consumers claim to be more knowledgeable than they actually are (Eberhardt, Kenning, and Schneider 2009). This variation also depends on the product nature (e.g. durable or search goods) and consumers' prior knowledge (Carlson et al 2009; Mehta, Hoegg, and Chakravarti 2011). Therefore, consumer researchers employ both terms to capture the degree of consumer product knowledge (Moorman et al 2004).

Business practitioners have traditionally regarded consumer product knowledge as a competitive advantage. This strategy seems intuitively appealing based on the assumption that more knowledgeable consumers show proportionately higher levels of interest on products due to higher confidence and knowledge assessment (Alba and Hutchinson 2000; Wood and Lynch 2002). Consumer product knowledge has been investigated across a wide range of product categories exhibiting considerable influence on information processing and decision making (Bettman and Park 1980; Brucks 1985; Carlson et al. 2009; Cowley and Mitchell 2003). From a marketing perspective disseminating knowledge regarding products may render them more attractive and therefore can have an impact on consumers' decisions. The main goal of consumers is to understand the product information in order to make a more educated choice. When consumers achieve that, they feel more confident about the quality of their decision and therefore feel more confident and evaluate their experience more positively. Additionally, improving consumers' knowledge can result in lower risk perception, both towards the focal products and the information provider (Brucks 1985; Dabholkar and Bagozzi 2002; Jiang and Benbasat 2007; Mittal and Sawhney 2001). As a result, the role of consumer product knowledge can be described as a vital link between accessed product information and consumers' further behavioral response.

Therefore, online firms which are increasingly challenged to advance product understanding to their consumers, often focus on strategies related to providing more and richer product information. Consumer product knowledge depends on the amount of the received information but, based on the cognitive load theory, too much information may reverse its effectiveness (Jacoby 1984). In addition, consumer product knowledge can be influence by the format and encoding of the information, a strategy which is increasingly feasible due to the emergence of advanced technologies (Jiang and Benbasat 2007). However, in some situations, neither the amount nor the presentation format of products can be influenced. This may happen due to lack of availability of additional information or limited resources or space (especially when the online provider is a product comparison website). We propose that in such cases, the differences in the composition of the choice set accessed by consumers may affect consumer product knowledge.

3.2.2 Choice Set Complexity

Decisions that consumers face on a regular basis entail a certain degree of complexity. The complexity of a choice is closely related to choice difficulty. Although these two constructs are closely related and treated as synonyms in the literature, choice complexity holds a rather objective perspective of the choice situation. Choice difficulty may differ across consumers that face even the same choice set and is related to the subjective assessment of the choice situation (Swait and Adamowicz 2001). The degree of choice difficulty occurs due to the need and the ability of consumers to counterpoise several aspects of costs and benefits derived from the available options. Inherently, higher choice complexity increases the decision maker's experienced difficulty. Choice difficulty is depicted by the amount of effort consumers put in making a choice (either from a cognitive or time perspective).

Choice complexity (as well as its antecedents and behavioral consequences) is widely investigated across various studies (Chatterjee and Heath 1996; Liberman and Forster 2006; Shugan 1980; Swait and Adamowicz 2001; Tversky and Shafir 1992). The complexity of a choice situation may be influenced by the number of alternatives and attributes (Scheibehenne, Greiffender, and Todd 2010). However, in practice, most of the times both the number of alternatives and attributes in a choice set presented remain consistent (same format) within a website. Keeping these two aspects constant, choice set complexity is reflected by the size of the attribute conflict as well as by the dispersion of the attribute values (Bettman et al. 1993; Chatterjee and Heath 1996; Moe 2006; Tversky and Shafir 1992).

The correlational structure of a choice set is essential since negative correlation increases the conflict associated with a choice (Dhar 1997; Luce 1998). Choices are considered more complex, the greater the required tradeoffs between attributes are. In principle, most choices encompass some tradeoffs between different product attributes of desirability and feasibility, such as quality versus price measures (Thompson, Hamilton, and Petrova 2009). A second component of choice complexity is the dispersion of the alternatives' attributes, which measures the degree of similarity of the alternatives. Larger dispersion of the attributes might signify more obvious differences among the alternatives and choices become more complex when this difference becomes smaller (DeShazo and Fermo 2002; Shugan 1980). In that case, consumers face a feeling of dissonance due to the fact that even the preferred choice set options are not clearly superior to other ones the choice feels less justifiable (Sela, Berger, and Liu 2009). However, we expect that greater attribute dispersion increases complexity in high conflict choice sets, since in such a case the differences in the trade-offs increase (Bettman, Johnson, and Payne 1990; Chatterjee and Heath 1996; Dellaert and Stremersch 2005; Festinger 1957). Given the existence of high conflict in the choice set, a higher distance of the attributes values, magnifies the size of the trade-offs needed.

In addition, choice complexity might be influenced by the level of relative attractiveness of the alternatives within a choice set as well as by the compatibility of the choice task (Nagpal and Krishnamurthy 2008; Tversky and Shafir 1992). Choices between equally attractive options increase the choice complexity compared to choices with equally unattractive options. Also, choice complexity can be influenced by the way and sequence the products are presented to the consumers (Novemsky et al 2007). Finally, the level of prior knowledge and product familiarity decreases the level of choice complexity (Brucks 1985; Dellaert and Stremersch 2005; Wood and Lynch 2002).

The level of choice complexity influences the decision making process of consumers. In complex choices the products are not easily distinguishable and therefore consumers find it hard to decide what to choose, decreasing their eagerness to make a final decision (Dhar 1997). In addition, complex choice sets require higher cognitive and time related effort (Johnson and Meyer 1989; Klein and Yadav 1989; Payne, Bettman and Johnson 1993). Decision difficulty can also have important negative implications for consumers' post-purchase evaluations of both the choice process and the chosen product (Dhar 1997; Jessup et al. 2009; Litt and Tormala 2010). Iyengar and Lepper (2000) showed that consumers who make a selection from a complex choice set report greater choice difficulty and less satisfaction than those who make a selection from a less complex choice set. Greater choice difficulty can have also objective pitfalls since it decreases consumers' decision quality (Dellaert, Donkers, and Van Soest 2012; Thompson, Hamilton, and Petrova 2009; Novemsky et al. 2007).

In general, the literature demonstrates the negative effects of choice complexity and highlights the need to simplify and assist consumers in their choices. Despite the obvious and intuitive negative aspect of choice complexity, a few studies attempted to highlight situations where this does not apply (Labroo and Kim 2009; Tsai and McGill 2011). Choice complexity, despite being considered as a burden to the decision, can be also regarded as greater investment and a signal of higher decision quality (Posheptsova, Labroo and Dhar 2010). An easy choice may mean lower effort but implicitly can signal insufficient effort invested in a goal and therefore may send the wrong signal (Tsai and McGill 2011). Also, in many cases, the amount of effort is used as a justification for the quality of the decision and based on this rationale products that are retrieved in a more difficult way may be evaluated higher because consumers want to compensate for the effort spent (Labroo and Kim 2009).

The sunk-cost fallacy can explain this decision rule that often enhances the value of a future event due to past investment (Arkes and Blumer 1985).

In order to give an alternative explanation on the mixed findings about the role of choice complexity, we introduce the construct of consumer product knowledge. We believe that the mechanism behind the objective and subjective knowledge formation differs. We propose that greater choice complexity increases objective consumer knowledge whereas it decreases consumer choice confidence lowering the subjective assessments of product knowledge.

3.2.3 Choice Set Complexity and Objective Product Knowledge

Conventional wisdom is replicated in expressions such as “No pain, no gain”. The underlying idea of such an expression is that harder work leads to greater rewards. When consumers are facing relatively complex choice sets they are expected to be involved in a more deliberate approach before making a choice (Klein and Yadav 1989). Also, consumers consider more attributes and attempt to conduct a more detailed comparative assessment in their product evaluations (Mehta, Hoegg, and Chakravarti 2011; Shugan 1980). As choice complexity increases, consumers’ reasoning process leads to a more thorough cognitive elaboration of the options in order to make the choice based on reasons (Sela, Berger, and Liu 2009). As a result, consumers are expected to improve their ability to assimilate greater information regarding the choice set when they make difficult trade-offs (Nagpal and Krishnamurthy 2008).

Research on numerical information elaboration showed that the time and effort required to compare two numbers is an inverse function of the numerical distance between them (distance effect) (Algom, Dekel, and Pansky 1996). Respectively, choice sets that include products that are closer together in terms of their attributes, require more time and therefore more cognitive effort to distinguish (Monroe and Lee 1999). Also, when consumers experience a complex choice, they activate a mechanism that seeks for reasoning in order to justify their choice (Shafir, Simonson, and Tversky 1993; Simonson and Nowlis 2000). The implied reason is that in such a case consumers think more deeply about the trade-offs in the choice set and they understand better their own preferences and purchase products that better fit their needs (Hoeffler and Ariely 1999). Less complex choice sets contain options that more clearly can outperform the other products in terms of overall utility. In such a case, consumers focus on the most promising product (i.e. the dominant option) since it is expected to entail the greatest relative benefits (given the costs) within the choice set. As a result, they accumulate information and focus on the specific product. As a result, consumers are involved in a rather myopic assessment of the choice set and only assimilate a part of the available information regarding the options and therefore, objective knowledge regarding the choice set decreases (Yoon and Simonson 2008). Therefore we expect that:

H1. *Higher choice complexity increases consumer objective product knowledge.*

3.2.4 Choice Set Complexity and Subjective Product Knowledge

Subjective knowledge is related to what consumers believe they know and is closely related to consumer self-confidence (Brucks 1985; Bearden, Hardesty, and Rose 2001; Carlson et al 2009). Choice complexity can reduce the feeling of confidence in consumers' judgments (Klein and Yadav 1989; Thompson, Hamilton, and Petrova 2009). Consumers, who find it more difficult to process product information from a choice set, are likely to feel more uncertain about the retrieved information than those who access information with more structured format (Gill, Swann, and Silvera 1998; Kelley and Lindsay 1993). Subjective knowledge is related to confidence and perceived difficulty of processing information (Schwarz 2004). Consumers report greater confidence when their subjective knowledge assessment is higher and when the environment is easy to evaluate (Tsai and McGill 2011). Several studies have found that individuals tend to be under-confident on complex tasks (Kruger 1999). This effect is known as the hard/easy effect (Billeter, Kalra, and Loewenstein 2011). Environments with easy choices make consumers feel secure (Hoeffler and Ariely 1999).

Choices inducing difficult trade-offs may lead consumers to believe that due to the complexity of the choice, they cannot achieve their goal and therefore their level of subjective knowledge drops (Hoeffler and Ariely 1999). Ease of choice leads to the feeling of confidence which results from the perception that the consumer ensured a desirable outcome without needing to put enough effort to the choice. Especially when consumers operate at lower construal levels, confidence is based on the feasibility of completing the task. Less complex choices may indicate that the choice task can be completed without hindrance. Respectively, complex choices signal a lack of ability to make the right choice, and indicate lower feasibility of completing the choice task, thereby reducing confidence (Tsai and McGill

2011). In addition, consumers have certain expectations about the products in a choice set, and these expectations direct them in their judgments. Violations of these expectations can lead to a feeling of uncertainty (Kahneman and Tversky 1982). Choice sets that are more complex and entail not easily distinct alternatives, have higher chances to create misattributions in consumer's judgment due to the closeness of the products' utilities.

H2. *Higher choice complexity decreases consumer subjective product knowledge.*

3.2.5 The Managerial Importance of Consumer Product Knowledge

In order to validate the managerial importance of consumer product knowledge, we also examine the effects of objective and subjective product knowledge on different behavioral outcomes. Higher product knowledge leads to superior performance in many contexts, including product information search and comprehension (Brucks 1985; Mehta, Hoegg, and Chakravarti 2011). When a consumer can remember many attributes of a product, then the likelihood of a positive attitude for that product is higher (Keller 1987). In order to describe such an effect, the availability, dominance of the given, and salience effect have been introduced to link product knowledge to product attitude (Hastie and Park 1986). Higher product knowledge reduces consumers' perceived risk, which is vital in determining actual consumer behavior (Alba and Hutchinson 2000). When consumers achieve a certain level of product understanding, they are more willing to make a buying decision (Aertsens et al. 2010). Therefore, we expect that objective product knowledge increases the probability of choice incidence. In addition, consumers are valuing more highly the chosen product when the level of choice complexity is higher (Kamins, Folkes, and Fedorikhin. 2009; Laran and Wilcox 2011). As a result, it is expected that higher objective product knowledge would lead to increased willingness to pay. Finally, objective product knowledge is correlated with increased choice satisfaction and confidence (Klein and Yadav 1989). The latter argument signals that there is a positive effect of objective knowledge on subjective product knowledge (Carlson et al. 2009).

Prior research suggested that subjective product knowledge affects decision making and can be a reliable predictor of attitude towards a stimulus and actual behavior (Luce, Jia, and Fischer 2003). Moreover, subjective knowledge can be a good indicator of attitude strength especially in search product categories which entail relatively high involvement and risk (Berger, Ratchford, and Haines 1994). Confidence in decision making increases the monetary amounts that gamblers are willing to bet, as well as the price buyers are willing to accept (Simmons and Nelson 2006; Thomas and Menon 2007; Tsai et al. 2008). When uncertainty about the choices is increasing, the willingness to pay decreases and the magnitude of this decrease becomes even greater in extreme uncertainty conditions (Okada 2010). Therefore, we expect that subjective product knowledge increases the willingness to pay for a product.

3.3 Study 1: Field Study with Financial Products

In the first study we test the proposed behavioral model of consumer product knowledge based on clickstream data from a financial product comparison website in Netherlands (in the house mortgages product category), combined with brief online surveys. Using the clickstream data[7], we could capture the choice complexity faced by each consumer as well as the actual behavior of consumers (i.e. decision time, conversion). The surveys (linked to the clickstream data with a unique ID number for every consumer) were used to collect additional data on consumer product knowledge. The surveys were appearing after the exit from the focal website (pop-under) in order to ensure that the knowledge questions were answered based on memory and not on copying the information. Questions were related to their previous visit to and experience on the website. The use of a financial product website (mortgages) allows for capturing consumer behavior across a set of multiattribute alternatives in a high involvement and durable product category. Therefore, consumer product knowledge is expected to have a highlighted role in the process.

3.3.1 Measures

Choice Set Complexity. Choice complexity was measured based on the actual composition of the choice set for each consumer (available from the clickstream data). Every consumer accessed a unique product choice set based on his personalized recommendations (given the specified amount of mortgage, income etc.). First, we measured the average interattribute correlation ($AttCorr_i$) across 3 product attributes in the choice sets (i.e. interest rate, quality and client ratings). Some of the correlation measures were reversed so that a positive value of interattribute correlation ($AttCorr_i$) depicts a less complex choice. The second component of choice set composition was the average range of the attributes ($AttRange_i$). A higher range signifies a larger distance of the attribute values across

[7] Clickstream data included information for every page visited by visitors followed with the respective time stamp. Also, all data provided by visitors was linked to their behavior through a unique ID number.

alternatives. However, we expect that greater range increases the complexity of a choice set when the interattribute correlation is negative. In that case, the expected trade-offs between alternatives are aggravated and therefore larger distance complicates consumers' decision. To capture this distinction, we used the interaction between interattribute correlation ($AttCorr_i$) and attribute range ($AttRange_i$).

Consumer Product Knowledge. Consumer product knowledge was measured based on two components. First, we measured objective product knowledge ($ObjKnow_i$) using a free recall test. After the end of their visit, consumers were asked to report in the survey the interest rate, quality score and brand of the first two products from their choice set as accurately as possible. Recall from memory is found to be a relatively good proxy of the actual objective knowledge (Kanwar, Grund, and Olson 1990; Khalifa and Lam 2002; Suh and Lee 2005). The recall test has been the most common method used for measuring price knowledge in the past (Eberhardt, Kenning, and Schneider 2009). We measured objective knowledge based on the percentage absolute deviation (PAD) instead of the percentage of exactly correct answers (due to the numeric values of the attributes, a slight mistake signifies higher recall than a totally unrelated price value)[8]. For interpretational reasons, we reversed the measures of PAD so that a higher value indicates higher objective product knowledge. Second, we measured subjective product knowledge ($SubjKnow_i$) in the online survey. Due to a practical limitation regarding the size of the pop-under survey, we used one question for the subjective assessment of knowledge ("how knowledgeable do you feel about the products offered in your visit to the website") (Moorman et al. 2004).

Website Conversion. The business model of the website used in this study is based on leads. Leads are customer requests for further information on a specific product. The website was receiving a fixed lead fee for every product for which the customer requested an offer. Hence we assume that from the website's point of view, conversion is achieved when the consumer makes a request for a proposal. Based on the clickstream data, we created a binary variable ($Order_i$) which takes the value of 1 when the consumer had made a request for a proposal and were directed to the actual provider (i.e. bank).

Additional Measures. From the clickstream data, we extracted information about consumers' income (self-filled). Also, based on a cookie identifier as well as IP address

[8] PAD is calculated as follows: Absolute value of the difference between actual and estimated price divided by the actual price. A greater difference between the answered value and the actual value results in a higher PAD, and, thus, indicates a lower level of objective product knowledge (Eberhardt, Kenning, and Schneider 2009).

information we measured repeated visits or choice sets for every consumer[9]. Finally, based on timestamps we measured the time spent by each visitor (as an indication of individual difficulty or interest).

3.3.2 Results

Descriptive Statistics. Participants were actual visitors of the financial website. A total of 243 visitors of the website filled in the online survey. The median annual income of the participants was 40 thousand euro. On average, participants spent approximately 6 minutes on their visit to the website. The average interattribute correlation ($AttCorr_i$) was 0.24 (ranging from -.86 to .73), which signifies a relatively low complexity choice set on average. The attribute dispersion ($AttRange_i$) ranges from 0.5 to 1.8 (mean=1.2). On average, objective knowledge score was moderately high (2.9 out of a maximum of 4) as well as the respective subjective measure (4.9 out of 7).

Objective Product Knowledge. First, we tested the effect of choice complexity on objective product knowledge. Objective product knowledge is not significantly affected by interattribute correlation ($\beta_{AttCorr}$=-1.40, t=1.31) but is significantly negatively affected by effect attribute range ($\beta_{AttRange}$=-1.21, t=3.35). The interaction between the two components of choice set complexity was negative and significant ($\beta_{Interaction}$=-1.92, t=2.00). This effect shows that when the interattribute correlation is negative (choice set becomes more complex), then objective product knowledge increases (given that the attribute range is always positive). Regarding the attribute range, though on average a higher range decreases objective knowledge, when the attribute correlation is negative, then objective knowledge increases. This is in line with our expectations regarding the complexity of a choice. In addition, we controlled for the amount of time spent looking for information (based on the rationale that more time of exposition on the informational stimuli would increase the ability to recall) but found no significant effect (β_{Time}=.21, t=1.65). Finally, neither repeated use of the website nor income were significant ($\beta_{ReturnVisit}$=-1.72, t=.85 / $\beta_{ReturnSet}$=-.20, t=1.17 / β_{Income}=-.07, t=.30).

Subjective Product Knowledge. First, we found a positive and significant effect of objective product knowledge ($\beta_{ObjKnow}$=0.18, t=2.02) on subjective knowledge. Conditional on this effect, no direct effect of either interattribute correlation or attribute range on subjective product knowledge was found significant. However, the interaction of the two choice complexity components was positive and significant ($\beta_{Interaction}$=2.78, t=2.14). The

[9] Some consumers used multiple specifications for their request regarding a mortgage (i.e. various periods, amount or type of mortgage).

positive sign of the interaction term shows that when a choice becomes more complex due to negative interattribute correlation (given that range is always positive), then subjective knowledge decreases. This negative effect becomes even stronger the greater the attribute range is. Conversely, when the attribute correlation is positive, greater attribute range increases subjective knowledge. We did not find any significant effect of time spent on a visit, income or repeated use of the website.

Further, we examined whether objective knowledge mediates the effect of choice set complexity on subjective product knowledge. Based on a bootstrap analysis (Preacher and Hayes 2008) the indirect effect of attribute correlation via objective knowledge is negative and significant (indirect effect = −0.10), with a 95% confidence interval excluding zero (−0.28 to −0.01), whereas the respective direct effect is positive and significant ($\beta_{AttrCorr}$=0.52, $p<.05$). Therefore, this is a case of competitive mediation (Zhao, Lynch, and Chen 2010). We found no mediating role of objective knowledge on the path between attribute range and subjective knowledge. Finally, regarding the effect of the interaction between attribute correlation and range, the indirect effect of the interaction term via objective knowledge is negative and significant (indirect effect = −0.09), with a 95% confidence interval excluding zero (−0.24 to −0.01), whereas the respective direct effect is positive and significant ($\beta_{AttrCorr}$=0.56, $p<.05$). Therefore, this is a case of competitive mediation (Zhao, Lynch, and Chen 2010).

Effects of Consumer Product Knowledge. In order to show that product knowledge is managerially meaningful, we examined its influence on website conversion. The results of a logit model specification showed a positive and significant effect of objective knowledge on website conversion ($\beta_{ObjKnow}$=0.55, $p<.01$). However, the effect of subjective knowledge on website conversion is not significant. In addition we tested the direct effect of choice complexity on website conversion. We found no direct effect of neither attribute correlation nor range on website conversion, but the interaction of these two components of choice set composition was positive and significant ($\beta_{Interacton}$=7.49, $p<.05$). This effect means that when interattribute correlation is negative (more complex choice set), the probability of making an order in the website is decreasing (to a larger extent, the greater the attribute range is). Conversely, when the attribute correlation is positive, the probability of converting is higher and increases with a greater attribute range. Finally, we found that time spent (β_{Time}=1.57, $p<.05$) as well as repeated use of the website ($\beta_{ReturnSet}$=.94, $p<.05$) both have positive effects on website conversion (indicating more involvement in the choice process).

Further, we tested whether product knowledge mediates the effect of choice set complexity on website conversion. Based on a bootstrap analysis (Preacher and Hayes 2008) the indirect effect of attribute correlation via objective knowledge is negative and significant (indirect effect = −0.28), with a 95% confidence interval excluding zero (−0.65 to −0.06), whereas the respective direct effect is positive and significant ($\beta_{AttrCorr}$=1.06, $p < .05$). Therefore, this is a case of competitive mediation (Zhao, Lynch, and Chen 2010). Respectively, we found no mediating role of subjective knowledge. Regarding attribute range, product knowledge has no mediating role on its effect on website conversion.

Table 3.1. Results of Field Study

Independent Variables	Dependent Variables for Study 1					
	Objective Knowledge		Subjective Knowledge		Website Conversion	
	Coef.	t	Coef.	t	Coef.	p
Intercept	**4.098**	**10.269**	**4.965**	**7.685**	**-4.208**	**.009**
Attribute Correlation	1.401	1.315	-2.538	-1.767	-6.974	.052
Attribute Range	**-1.210**	**-3.350**	-.341	-.687	1.889	.097
Att. Correlation * Att. Range	**-1.921**	**-1.999**	**2.784**	**2.137**	**7.485**	**.021**
Time	.214	1.647	.190	1.080	**1.569**	**.015**
Return Visit	-.074	-.304	-.441	-1.347	**.937**	**.024**
Return Set	-.203	-1.169	-.357	-1.521	**.387**	**.028**
Income	-.172	-.849	.526	1.925	-1.206	.482
Objective Knowledge			**.178**	**2.024**	**.546**	**.003**
Subjective Knowledge					-.094	.462
R^2	**.12**		**.09**		**.18 (Nagelkerke)**	

3.3.3 Discussion

The findings of Study 1 suggest that higher choice set complexity increases objective product knowledge and decreases subjective product knowledge. The low R^2 (in the models of objective and subjective knowledge) may be attributed to the cross sectional nature of the data (given the size of the sample), but also to an inherent ability of retaining information in some individuals. In addition, we show that product knowledge is managerially meaningful in that it does influence website conversion. We conducted this study in a realistic setting of a financial product comparison website where choice sets were based on consumers' idiosyncratic preferences. While such an approach has the advantage of external validity, we cannot ignore the amount of noise it hinders due to exogenous factors (e.g. no control for task involevement). The choice set composition was unique for every visitor and therefore some of the findings might be driven by the variance in choice set characteristics (e.g. overall choice set utility). Since on average, choice sets were moderately complex, it would be insightful to investigate the effects on product knowledge in more controlled environments and including a larger variation in complexity. In this way, we could be able to inspect and compare easy versus more complex decisions. We address these limitations in a more controlled environment in study 2.

3.4 Study 2: Experimental Study in Consumer Electronics

The purpose of this survey based experimental study was to test the proposed behavioral model of choice complexity and consumer product knowledge in a more controlled setting. To that end, we manipulated choice complexity in a clear and distinguishable manner (ranging from easy to rather complex choices). Moreover, participants were asked to assess a price they were willing to pay for their most attractive option from the choice set. Moreover, the product category is different than study 1. In order to increase the generalizability of our findings, we applied our framework in a different product category (consumer electronics). In this case, the focal products were less expensive and with a stronger hedonic perspective.

The design of the experiment was as follows. First, respondents had to reply to some questions related to their familiarity with the product (digital photo frames). Then, they were told that they were given a coupon from a website[10] and they could pick one of the products from the offered choice set, or wait for the following day for a different choice set (however the current choice set would not be available anymore). Then they had to pick the most attractive product from the choice set and then state whether they would buy this product or they would prefer to wait for another choice set (or get the equivalent of half of the digital photo frame price in the market instead). The following step was to reply to some product knowledge related questions. In order to make respondents' choices more consequential, we introduced in the end an incentives-compatible task to measure their willingness to pay.

3.4.1 Measures

Choice Set Complexity. Choice complexity was measured in a similar way to study 1. The attributes used in this study were a rating score (measured in a scale from 0 to 5), the memory size and the resolution (in pixels) of the photo frames. The choice complexity was

[10] In such a way, we wanted to minimize the effect of price on their decisions.

manipulated across interattribute correlation (AttCorr) and range of the attributes (AttRange) in the choice sets. We used 4 distinct categories for the interattribute correlation[11]. The first 2 conditions had a negative correlation (strong versus weak) and the latter 2 conditions had a positive correlation (strong versus weak). In terms of range, we created 2 conditions with high versus low range. In Table 3.2 you can find an overview of the conditions. We created the 4*2 conditions in such a way that the overall attractiveness of all choice sets was almost identical (between 6.1-6.3 out of 10).

Consumer Product Knowledge. Similarly to study 1, consumer knowledge was measured both in terms of objective and subjective measures. We measured objective product knowledge using a free recall test. We measured objective knowledge based on the percentage absolute deviation (PAD). For interpretational reasons, we reversed the measures of PAD so that a higher value indicates higher objective product knowledge. Second, we measured subjective product knowledge based on a scale adapted from Moorman et al. (2004).

Table 3.2. Experimental Manipulations

Attribute Correlation	High Negative		-0.45
	Low Negative		-0.2
	Low Positive		0.2
	High Positive		0.45
Attribute Range	Rating Score	Low	3.0-4.0
		High	2.5-4.5
	Memory	Low	256MB - 800MB
		High	128MB - 1024MB
	Resolution	Low	430*234 - 712*480 pixels
		High	320*234 - 800*600 pixels

Website Conversion. Respondents had to decide whether they wanted to get one of the products from the accessed choice set, or if they would rather wait for another set of products (losing the chance to get one of the products of the current choice set). In case respondents chose one of the products from the choice set, we assume that conversion has achieved.

Willingness to Pay. In order to measure willingness to pay, we used an incentive-aligned method called "BDM" (Becker, DeGroot, and Marschak 1964; Wertenbroch and Skiera 2002). Respondents were informed that in the last part of the task, they would have the

[11] Correlation between rating score and memory size.

chance to win the product of their choice. They were asked to state the maximum price they would be willing to pay for their chosen product. Then a random price would be drawn[12]. If that randomly selected price was equal to or lower than the respondents' stated price, they would receive the actual product and the monetary value of the difference between a maximum price (100 euro) minus their stated price[13]. Otherwise, they would get a substantially lower amount of money[14]. Since the random drawn price is not known or influenced by the respondents, it was ensured that it would be in the respondents' best interest to reveal their actual maximum price for the chosen product. Before we ask the respondents their actual stated price, we simulated some examples and checked whether they correctly understood the process. Only when they found the correct answer to the examples given, they were able to participate in this task.

Additional Measures. We measured the familiarity of the respondents with the product category based on a scale adapted from Ho and Tam 2011. We also measured some demographic characteristics of the respondents (i.e. gender, age, income). Moreover, we tracked the time (in seconds) it took every respondent to make a choice regarding the most attractive product and whether he would like to get it now or wait for the next choice set. Finally, we measured the decision quality based on the rank of the chosen product in the choice set based on the overall utility (based on equal weights of each attribute).

3.4.2 Results

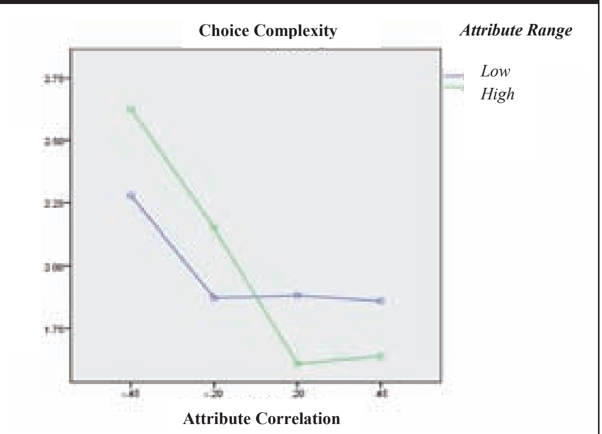
Descriptive Statistics. A total of 711 respondents which were members of an Internet-based research panel filled in the survey (out of which 538 successfully completed the willingness to pay task). Respondents were mostly females (57%), with an average age of 43 years and a monthly income of approximately 2.200 euro. On average, participants spent approximately 3 minutes to make their choice and in total 16 minutes to complete the study. The number of respondents across the experimental conditions was balanced (10%-15% in each of the 8 conditions). Regarding the product knowledge scores, the average objective knowledge score was quite high (7.2 out of a maximum of 10) and the respective subjective

[12] Due to data collection constraints, one single random price was drawn for all respondents. However, we believe that this approach would not influence the results.
[13] The original method required that participants would have to pay their stated price in case their stated price was higher than the draw. In our approach, that was not possible. This is why we adapted the payoff method.
[14] Those who don't want the product would still prefer the lower amount. If the outside option had an equal value, more respondents would incline to put a low price in order to get the money. Since we do not force people to pay for the product, we believe we can stll get a good impression of those who indeed like the product.

knowledge average was moderate (2.8 out of 6). Finally, the average willingness to pay was 37 euro (given a reference price of 60 euro in the market, stated in the description of the situation).

Manipulation Checks. To check for the manipulation of choice set complexity, we asked the respondents to state the perceived difficulty of the choice set they faced. To measure this construct, we used 4 statements based on their perceived difficulty and certainty (reversed to capture difficulty) of their decision and which were loaded in one factor (AVE=.75; Cronbach's alpha=.81). The higher the attribute correlation (shifting from very negative to very positive), the lower the perceived difficulty of the respondents ($t=11.86$, $p<0.01$), suggesting a successful manipulation of the attribute correlation in terms complexity. In addition, though there was no significant difference between low and high attribute range, the interaction between attribute correlation and range was significant ($t=6.32$, $p<0.01$). The following figure illustrates the fact that higher attribute range renders a choice set more difficult when the attribute correlation is negative, whereas it has the opposite effect when attribute correlation becomes positive.

Figure 3.1. Manipulation Check of Choice Complexity



Objective Product Knowledge. First, we tested the effect of choice complexity on objective product knowledge. Objective product knowledge is directly affected by both the attribute correlation ($\beta_{AttCorr}$=-.134, $t=2.19$) and attribute range ($\beta_{AttRange}$=-1.07, $t=8.13$). However, the interaction between the two components of choice set complexity was not significant ($\beta_{Interaction}$= -.14, $t=1.12$). These results show that the more complex a choice is in terms of attribute correlation, the higher the consumer product knowledge is. The same applies for larger dispersion of the attributes, regardless the sign and size of the conflict in the choice set. In addition, we controlled for the amount of time spent to make a choice (based on the rationale that more exposition on the choice set would increase the ability to recall) and found a positive and significant effect (β_{Time}=.002, t=3.37). Also, there was no significant effect of familiarity (all 4 statements were loaded in one factor; AVE=.85, Cronbach's alpha=.87). Finally, regarding demographic characteristics, only age had a significant effect on objective product knowledge (β_{Age}=-0.04, t=7.72).

Subjective Product Knowledge. We found no direct significant effect of attribute correlation on subjective knowledge but the direct effect of attribute range was found significant (β_{Range}=.18, t=2.15). The interaction of the two choice complexity components was positive ($\beta_{Interaction}$=2.78, t=2.14). This positive sign signifies that when a choice becomes more complex due to negative interattribute correlation, subjective knowledge decreases. This effect becomes even stronger when attribute range increases. We found no significant effect of time spent or income on subjective knowledge. However, we found higher subjective knowledge on females (β_{Gender}=.22, t=2.58), younger respondents (β_{Age}=-.01, t=2.11) and those who were more familiar with the product category ($\beta_{Familiarity}$=.50, t=17.80). Finally, we found a positive and significant effect of objective product knowledge ($\beta_{ObjKnow}$=0.10, t=4.17). Based on a bootstrap analysis (Preacher and Hayes 2008), we found that the indirect effect of attribute correlation via objective knowledge is negative and significant (indirect effect = −0.02), with a 95% confidence interval excluding zero (−0.04 to −0.01), whereas the respective direct effect is not significant ($\beta_{AttrCorr}$=0.06, $p > .05$). Therefore, this is a case of indirect only mediation (indirect effect exists but direct effect does not) (Zhao, Lynch, and Chen 2010). We found no mediating role of objective knowledge on the path between attribute range or the interaction term and subjective knowledge.

Effects of Consumer Product Knowledge. Similarly to the first study, we examined the managerial importance of the two components of consumer product knowledge. First, we used website conversion as a behavioral outcome. The results of a logit model specification showed a positive and significant effect of objective knowledge on website conversion ($\beta_{ObjKnow}$=0.09, $p<.01$). In addition, the effect of subjective knowledge was also significant ($\beta_{SubjKnow}$=0.15, $p<.01$). Furthermore, we tested the direct effect of choice complexity on conversion. However, only the direct effect of attribute correlation was found positive and significant ($\beta_{AttCorr}$=0.14, p=.05). This effect means that a more complex choice (when attribute correlation is negative), the probability of making a choice is lower (choice deferral is higher). Regarding the individual characteristics, only gender significantly influences conversion (β_{Gender}=-0.44, p<.05).

Table 3.3. Results of Experimental Study								
Independent Variables	**Dependent Variables Study 2**							
	Objective Knowledge		Subjective Knowledge		Website Conversion		Willingness to Pay	
	Coef.	*t*	*Coef.*	*t*	*Coef.*	*p*	*Coef.*	*t*
Intercept	**8.127**	**34.49**	**.904**	**2.074**	**-.739**	**.012**	**24.85**	**3.694**
Attribute Correlation	**-.134**	**-2.193**	.060	1.622	**.144**	**.050**	-.116	-.215
Attribute Range	**-1.069**	**-8.134**	**.178**	**2.154**	.248	.133	**-2.627**	**-2.119**
Att. Correlation * Att. Range	-.138	-1.122	**.148**	**1.989**	.108	.467	**-2.171**	**-1.988**
Time	**.002**	**3.374**	.000	.613	.000	.840	.002	.471
Gender	-.007	-.053	**.221**	**2.579**	**-.442**	**.010**	**-3.888**	**-3.083**
Age	**-.035**	**-7.722**	**-.006**	**-2.114**	.009	.125	.059	1.385
Income	.088	1.805	-.007	-.234	.034	.560	.498	1.164
Familiarity	.048	1.036	**.495**	**17.80**	-.081	.221	.754	1.476
Objective Knowledge			**.095**	**4.174**	**.092**	**.041**	.614	1.669
Subjective Knowledge					**.147**	**.049**	**1.252**	**2.183**
R^2	**.18**		**.37**		**.04**		**.07**	

Further, we tested the effects of consumer product knowledge on the respondents' stated willingness to pay, according to the incentives-compatible task of our study. We found a positive and significant effect of subjective product knowledge on willingness to pay ($\beta_{SubjKnow}$=1.25, t=2.18). Respondents who were feeling more knowledgeable regarding the options offered in their choice task were willing to pay more for their chosen option. The effect of objective knowledge had no significant effect on willingness to pay ($\beta_{ObjKnow}$=0.61, t=1.67). However, based on a mediation analysis, the effect of objective knowledge on willingness to pay is mediated by subjective knowledge (indirect effect = 0.14 with 95% confidence interval between 0.03 and 0.33) (Preacher and Hayes 2008). The direct effect of objective knowledge is positive ($\beta_{ObjKnow}$=0.84, t=2.44) (competitive mediation based on Zhao, Lynch, and Chen 2010). Also, regarding the direct effect of choice set complexity on willingness to pay, we found a negative effect of the interaction between attribute correlation and attribute range ($\beta_{Interaction}$=-2.17, t=1.99). This finding shows that when attribute correlation is positive (less complex choice set) the willingness to pay for the chosen product is lower (this effect is aggravated when range is high). This may be attributed to the fact that respondents value higher a product for which they invested more effort to choose. An additional mediation analysis revealed a significant negative indirect effect of attribute correlation through the successive path of objective and subjective knowledge ($AttCorr_{Indirect}$= -0.02, only-indirect mediation) (Zhao, Lynch, and Chen 2010). Finally, regarding the control variables, similarly to the effects on conversion, only gender had a significant effect (β_{Gender}=-3.89, t=3.08).

3.4.3. Discussion.

The findings of Study 2 provide validation for the expected relationship between choice complexity and consumer product knowledge. In addition, the consistency of the effect across both studies highlights the importance of consumer product knowledge across different product categories and settings. Although the components of consumer product knowledge are affected by choice set complexity in an opposite way, both influence in turn the conversion and willingness to pay.

3.5 General Discussion

We have presented a framework of how differences in the composition of the product choice sets can influence consumer product knowledge. These differences correspond to the degree of choice set complexity. Consumer decision making is taking place in environments that invoke a certain degree of choice complexity and uncertainty. We propose that choice set complexity increases objective consumer knowledge due to increased deliberation of the consumers whereas it decreases consumer confidence and hence, their subjective knowledge assessment.

Evidence from two studies provides strong support for this theoretical framework. First, we show that increased choice set complexity (captured by the degree and size of conflict) increases the ability of consumers to remember the components of the choice set they have encountered. However, this positive effect of complexity is overshadowed by the decreased subjective knowledge when choice sets become more complex. In addition, we also found a competitive mediation of objective knowledge on the abovementioned relationship. In addition, our results give some indication on the managerial importance of consumer product knowledge on the decision to convert as well as on the willingness to pay for the chosen alternative. However the R^2 regarding willingness to buy was low. Although R^2 values are low in cross sectional data (and also in small samples), this low number indicates that there are other important factors influencing the willingness to pay (e.g. perceived quality of the product). Finally, we found some evidence regarding the mediating role of consumer product knowledge (both objective and subjective) on the relationship between the elements of choice set complexity and the final choices of the consumers.

This study enhances our understanding about the antecedents of consumer product knowledge. We show that consumer knowledge can be improved by changes on the composition of the offered choice set. However, whereas we show that complexity is not necessarily unfavorable since it increases objective product knowledge, companies need to be aware of the conflicting negative effect of complexity on subjective knowledge. This contradiction offers additional support on the current assumption that the two components of consumer knowledge should be disentangled. Also, we validate that the effect of choice set complexity on consumer product knowledge is managerially meaningful in providing evidence for its influence on consumer conversion and willingness to pay for the chosen alternative. Finally, we provide a more generalizable framework by finding support of our expected relationships in two distinct product categories and across distinct methods of data collection.

3.5.1 Practical Implications

Based on the findings of the current study, companies can benefit by gaining deeper insights on the mechanism behind consumer knowledge. It is very important for companies to understand how to improve the product understanding of their customers without additional costs and investments. An introduction of more content in describing the products offered might lead to high cognitive load for the consumers and may be even neglected by them. Also, a more interactive way to disseminate the information about the product offerings might be beneficial (Jiang and Benbasat 2007; Suh and Lee 2005) but it requires substantial costs to implement and additional training of the users. However, we propose that consumer product knowledge can be improved by manipulated the composition of the offered choice set. Naturally companies attempt to facilitate the decision making process of their consumers. However, this approach can be outshined by the decreased objective knowledge of the consumers in increasingly easy choice environments. Conversely, by increasing the choice set complexity though, consumers feeling of knowing declines. In complex choice sets, consumers might be able to absorb better the information, but they feel less confident about it. As a result, companies should investigate the optimal point of this trade-off between objective and subjective knowledge[15].

In addition, we provide evidence about the managerial importance of the components of consumer product knowledge. Both objective and subjective knowledge positively influence the decision to buy but also the value assigned to the most attractive product. This effect signals the need for relative more complex choice sets that increase what consumers know and indirectly can influence how they feel about it. This means that making the choice more effortful to the consumers, increases how they perceive the experience and might attribute higher value to a product which under easy environments would not equally appreciate. However, this approach would lead to suboptimal choice sets that do not necessarily represent the best composition in terms of overall fit between the company's offers and the consumer's needs.

3.5.2 Limitations and Future Research

Although we recognize the limitations of using recall for operationalizing content product knowledge, past research showed that recall tests can highly approximate the actual knowledge (Kanwar, Grund, and Olson 1990). However, recall is related to short-term memory effect and it would be insightful to examine whether the amount of objective knowledge remains in a more long term time span. A way to confront this issue could be to repeat the recall test at a later point in time.

Also, regarding choice set complexity, it would be interesting to introduce additional components such as the number of the alternatives or attributes presented to the consumers, or the relative attractiveness of the choice set (Nagpal and Krishnamurthy 2008). One additional potential limitation is that the effect of choice set complexity may be non-linear and that there are different outcomes in more extreme conditions. For example, when a choice set becomes extremely complex, consumers might start using compensatory heuristics in order to facilitate their choice process. As a result, objective knowledge would decrease and the confidence of their subjective knowledge is expected to improve.

Finally, it would be interesting to examine the effects of choice set complexity as well as consumer product knowledge on different behavioral outcomes of the consumers. It is expected that consumer knowledge would increase the decision quality and satisfaction of the consumers. However, the influence of choice set complexity on these outcomes would highly depend on the weight that implicitly consumers assign to the subjective knowledge.

[15] A simulation showed that the optimal point in terms of maximum conversion probability given the results of the second study is in the case of positive correlation and low range.

Όποιος βιάζεται σκοντάφτει (Haste makes waste)
Το γοργόν και χάριν έχει (A favour done quickly is twice done)
Σπεύδε βραδέως (More haste, less speed)
Greek Proverbs

Chapter 4

The Opposing Effects of Product and Choice Set Level Inspection Time on Recommendation Website Conversion

4.1 Introduction

Online consumers have easy access to a vast array of information and can easily visit many websites before deciding what and where to buy. The low online search costs reduce switching barriers between product providers and increase total search on the internet (Lynch and Ariely 2000). Many online firms are also confronted with low conversion rates[16] (Moe and Fader 2004). To resolve these issues, firms attempt to make their websites "sticky" to visitors for example by offering extensive product information and interactions (Murray and Häubl 2007). One of the key measures of stickiness is the average duration of consumers' website visits. The rationale is that the longer consumers are browsing a website, the more likely it is that they find what they want and decide to make a purchase (Bucklin and Sismeiro 2003; Danaher, Mullarkey, and Essegaier 2006; Moe 2003). Paradoxically however, firms have also benefitted from shortening online consumer shopping time by making it more effective for consumer to find the products that they want, e.g., through the use of product recommendations (Wang and Benbasat 2005; Xiao and Benbasat 2007). Product recommendations decrease the time consumers need to spend to find an attractive alternative online (Häubl and Trifts 2000; Todd and Benbasat 1994). In this case, spending less time online -because it reflects decreased consumer effort- positively affects website conversion rates (Johnson, Bellman and Lohse 2003).

These opposing effects of online inspection time on website conversion raise the question if making product recommendation website more "sticky" is beneficial or not. In

[16] Number of visitors who made a purchase (converted into buyers) divided by the otal number of visitors.

this study we begin to resolve this issue by disentangling consumer inspection time into two components that are hypothesized to have opposing effects on website conversion: product and choice set level inspection time. At the product level we expect that increases in inspection time increase the chance of website conversion. This is the case because spending more time to inspect a given alternative in greater detail indicates a higher expected utility of searching for information on this alternative, which is positively correlated with the attractiveness of the alternative (Kim, Albuquerque, and Bronnenberg 2010; Xu & Kim 2008).

At the choice set level, we predict that increases in inspection time decrease product recommendation website conversion. The underlying reason is that at the choice set level, increases in time spent comparing different alternatives are determined by the complexity of the recommended set, which harms conversion rates. In this case the amount of time spent comparing alternatives is an indication of the difficulty of selecting the best alternative from a choice set and of choice uncertainty (Dellaert, Donkers, and Van Soest 2012; Haaijer, Kamakura, and Wedel 2000; Otter, Allenby, and Van Zandt 2008).

Hence we propose that whereas greater choice set inspection time is driven by the challenges of a complex decision task, and has a negative influence on product recommendation website conversion, greater product-level inspection time reflects a higher expected product utility and has positive effect on website conversion. We analyze clickstream data from 9,473 consumers using a mortgage product recommendations website[17] to empirically investigate these proposed opposing effects of choice set and product level inspection times on website conversion.

4.2 The Concept of Time in Decision-Making

The construct of time spent on pre-purchase stages has been incorporated into economic theories (Becker 1965; Stigler 1961) as well as consumer behavior and psychology studies (Jacoby, Szybillo and Berning 1976; Lanzetta 1963). In general, time has been used as a proxy of effort in the pre-purchase process, in the form of the total time spent by consumers until the completion of their search task (Bucklin and Sismeiro 2003; Häubl and Murray 2003; Lurie 2004). A further distinction was made by using time as a measure of depth of search (time spent in evaluating information on a single alternative) and breadth of the search (expressed in terms of the number of alternatives examined or the total time spent across all alternatives) (Bettman et al. 1993; Bettman, Johnson, and Payne 1990; Jacoby,

[17] Same website as in study 1 of chapter 3.

Szybillo and Berning 1976). In this line of research, response latencies were introduced as predictors of consumer preferences (Aaker et al.1980; Busemeyer and Townsend 1993; Haaijer, Kamakura, and Wedel 2000). Response latencies capture the time needed until the point a consumer makes a decision and indicates in a way the amount of effort needed to make a decision (Bettman, Johnson, and Payne 1990; Roberts and Lattin 1991).

Decision time observations have become instrumental for online firms in order to predict their conversion rates. Recent research supports the view that a longer website visit times are positively correlated with conversion (Bucklin and Sismeiro 2003; Danaher, Mullarkey, and Essegaier 2006; Lin et al. 2010; Huang, Lurie, and Mitra 2009) as well as transaction volume (Zott, Amit, and Donlevy 2000). The underlying rationale is that the duration of the website visit increases for more attractive websites which show higher retention and online conversion rates (Agarwal and Venkatesh 2002; Bansal et al. 2004). Thus, more time spent on a website is an indication of greater engagement and involvement of the consumer (Moe 2003) but also of the attractiveness of the website. Following this perspective, more time spent on a website also correlates with a higher level of flow of the consumers (Hoffman and Novak 2003; Xu and Kim 2008). The amount of time a consumer spends on a website over a certain period (website stickiness) as well as in a given visiting session (session stickiness) are related to the website's ability to prolong online customers' session duration and can be a good indication of consumers' intention to transact with the website (Bhatnagar and Ghose 2004; Lin 2007; Lin et al 2010). Finally, more time spent on a website leads to greater amounts of information and lower decision uncertainty (Urbany, Dickson and Wilkie 1989). These findings support the positive effects of total inspection time on website conversion and explain why high advertising fees are asked by websites with longer average visit duration (Wolk and Theyson 2007).

Besides the abundance of studies demonstrating an advantageous role of decision time on conversion, there are also studies that have differently concluded. Consumers are quite sensitive to the search costs which, especially in an online environment, are mainly non-monetary and related to time and effort (Häubl, Dellaert, and Donkers 2010). Consumers are susceptible to these non-monetary time costs since they comprise an integral part of the effort needed from them (Berry 1979). Consumers are expected to stop searching when the expected benefits of more search do not cover the marginal cost (effort) of keep searching. Diehl (2005) found that spending a lot of time searching for products in ordered lists can degenerate the quality of consumers' decisions. Lower decision time in a website may signify an easy decision in which at least one of the alternatives is outstanding, and higher decision duration therefore points to more complex decisions (Otter, Allenby and Van Zandt 2008). In addition, more experienced searchers may become keener to invest more time due to their confidence of eventual success, but also their visits may become shorter due to the power law of practice (Johnson, Bellman and Lohse 2003; Ward 2000). Therefore, lower decision time may show greater decision efficiency as a result of increased learning efficiency. Accordingly, visitors who spend less time on a website may be more likely to convert to purchases since they may show lower cognitive costs and higher efficiency in search (Johnson, Bellman, and Lohse 2003; Lin 2010). Therefore, whereas consumer involvement and expertise both increase the purchase likelihood, they have opposite effects on total time spent. Consequently, the net effect of decision time is ambiguous and in some cases more time is more efficient whereas in some other cases it signals lack of efficiency.

Figure 4.1 Illustration of Inspection Type Dimensions

Choice Set Level Inspection Time	Product level Inspection Time

Note: Print Screens were taken from Walmart.com

4.3. Inspection Time and Recommendation Website Conversion

In order to explain these opposing effects of online inspection time, we propose a disentanglement of total time spent on a recommendation site. Whereas in previous studies, decision time was treated as a one-dimensional construct, only a few researchers attempted to decompose total decision time into various components according to different stages of the decision process (e.g. information search, evaluation of alternatives, purchase decision). The underlying rationale of these distinctions has its base in economic theories positing that different types of time are expected to have different effects on choices and behavior. In particular, total response time for a decision problem has been divided into input (time to process information), decision (deliberation time before choice) and motor time (physical reaction time) (Kiesler 1966; Stone 1960). An additional distinction of total time consists of problem time (presentation of the problem), query time (time between first and last request of information) and decision time (time between last information request and final decision) (Pollay 1970). All the above distinctions of decision time have a common foundation. The total time of an episode can be divided into the time the consumer needs to collect the required information for the alternatives and the time the consumer needs to make a decision. Based on this foundation we propose a distinction of total inspection time into the time spent on a product level and choice set level inspection and the remaining "other" time that captures a variety of aspects such as time needed to complete online forms, explore non-product or choice set related information, or to place an order. Product inspection time can be defined as the time spent studying detailed information for a specific alternative (Konstan et al. 1997; Xu and Kim 2008). Choice set inspection time is the time spent comparing multiple alternatives that are viewed at the same time (Marmorstein, Grewal, and Fishe 1992). In the following section, we describe in detail the different aspects of time spent in these different processes.

4.3.2 Product Level Inspection Time

We investigate a typical product recommendations website where consumers face a web page with a list of products based on their requested specifications. Usually some information about the alternatives is accessible in this main page, but this information typically is restricted to only some basic factual information (i.e. price, quality, and brand) which may not be sufficient for consumers in order to draw their conclusions and make a choice. Therefore, visitors of a website can request additional information for each specific alternative, for example by clicking on a page link with additional information for the requested product. This additional information may be an extension of the factual information and also include more experiential information (e.g., customer or expert reviews). In this study, we define the time spent on such a page as inspection time.

The rationale for considering product level inspection time as a separate part of total decision time originates from the notion of knowledge uncertainty (Urbany, Dickson and Wilkie 1989). Product inspection time helps overcome knowledge uncertainty, i.e., the uncertainty that is caused by the fact that consumers have incomplete knowledge about an alternative (Urbany, Dickson and Wilkie 1989).This uncertainty leads consumers acquiring more information about the alternatives that are on offer by the seller (Lin et al 2010)[18]. In doing so, consumers have to take two distinct decisions: which product to inspect and how much effort to invest in this product. Meyer (1982) described these choices as inspection decision and effort respectively. The power law of practice is decreasing decision time due to the high efficiency and familiarity accumulated after repeated uses of the website (Johnson, Bellman and Lohse 2003). Therefore, experienced visitors are able to make faster choices based on fewer inspections of products (since they can easily identify the best options). Product level inspection time seems to not be affected by this law since it reflects the level of interest and involvement towards the inspected product (Mobasher et al. 2001; Lin et al. 2010).

Although before inspection, some attribute information may be available, consumers tend to infer that products superior on the observable attributes are also expected to be superior on the unobservable attributes as well (Chernev and Carpenter 2001). Therefore, the expected utility from a product's inspection can be modelled as a function of its observable attributes (Moe 2006). The amount of time spent by users on a product page is based on the user's interest on the page as well as the content of the page (Mobasher et al. 2001). Therefore, longer product level inspection times signify favorable product attributes and better match of their preferences (Xu and Kim 2008). The attractiveness of a product is related to price, quality and brand related attributes. Lower price related attributes of a product lead a consumer to make more effort to collect additional information about the product. Quality measures are often observable in product lists making these products to be inspected in a more effortful way (Ordonez 1998). The reason is that higher quality ratings can lead to more favorable decisions which can increase the expected benefit from inspection. Therefore, the more positive the quality rating of a product is, the more likely is a consumer to make an effort to collect additional information about it (Senecal and Nantel 2004; Xu and Kim 2008). Brand information in a product list is a substantial attribute which consumers often take into consideration during the search process. Particularly for less experienced consumers, the dependence on brand information is driving expectations regarding unobserved information (Ward 2000).

[18] Lin et al (2010) used the term "content gathering time" to describe the time spent for accessing information about particular products.

Similarly to an information search context where consumers invest more time in viewing more relevant information, in a shopping context, consumers spend more time looking at relevant items that better match their needs. Thus, inspection time is an indication of consumer preferences, or purchase propensity (Chorus and Timmermans 2007). Since inspection effort is often biased towards more attractive products, consumers are more likely to come across positive feedback from the inspected product and the positive valence of this feedback has a higher likelihood to lead to persuasion (Kisielius and Sternthal 1984; Xu and Kim 2008). The utility of an alternative increases with the amount of information collected since perceived uncertainty of this option is reduced (Meyer 1982). Since knowledge uncertainty is essential in online searches, reducing uncertainty about the alternatives has a positive effect on purchase intention (Hauser, Urban and, Weinberg 1993; Urbany, Dickson and Wilkie 1989; Xu and Kim 2008). In addition, a longer time duration spent on inspecting specific alternatives from the choice set reflects a higher level of involvement in the search process. Consumers who invest a lot of effort in inspecting products are expected to have a higher willingness to reach a final decision. Dissonance theory predicts that respondents make a retrospective justification of the effort they put and evaluate the goal more positively the more effort they put into it (Festinger 1957). This suggests that an alternative would be chosen more if more effort has been put into its inspection.

Therefore, we expect that there is a positive relationship between product level inspection time and website conversion. The underlying reason for that effect is that higher product level inspection time is driven by higher attractiveness of the alternatives in the choice set.

4.2.3 Choice Set Level Inspection Time

Information search is characterized by a sequence of decisions that consumers have to take regarding which products to inspect and purchase (or whether to purchase at all). The uncertainty revolving around these decisions is known as choice uncertainty (Lanzetta 1963; Urbany, Dickson and Wilkie 1989). Choice uncertainty increases as the risk of not choosing the best option increases and as a result consumers increase the cognitive effort needed in order to make a decision. The effort is captured by the time they need until they decide which option to inspect or purchase. This aspect of total decision time is considered as the choice set level inspection time. Choice set level inspection time is related to the concept of deliberation time in a comparison shopping context (Marmorstein, Grewal, and Fishe 1992; Putsis and Srinivasan 1994). The underlying driver of choice set level inspection time is the uncertainty caused by the choice complexity. The more complex a choice is, the longer the choice set level inspection time needed is. Although at minimal levels, it may be expected to increase conversion rate, soon it becomes a burden for making a final choice.

Research has showed that the complexity of a choice set is highly related to choice deferral (Dhar 1996; Dhar and Nowlis 1999; Scheibehenne, Greiffender, and Todd 2010). Past literature has examined the effects of complexity of the choice environment on the duration of the time spent choosing and highlighted the importance of the trade-off between accuracy of choice and effort spent (in terms of time spent reaching a final purchase decision) (Fasolo, McClelland, and Todd 2007). When the structure of the choice set becomes more complex, consumers put additional effort in order to deliberate all the information they possess and reach a conclusion. Consumers prolong the search until they maximize the expected benefits of their choice and therefore, longer choice set level inspection time indicates a higher deliberation of the possible outcomes of the decision (Haaijer, Kamakura, and Wedel 2000). In addition, choice complexity can generate a negative emotional state of anxiety which can also lead to a prolongation of the decision time (Luce 1998). The complexity of a choice set depends on the trade-offs among the alternatives as well as on the degree of similarity within the choice set.

The first component of choice complexity relates to the interattribute correlation in the choice set. The correlational structure of the choice set is essential because negative correlation increases the conflict associated with a choice. When the correlation between alternatives' attribute levels is positive, the relative attractiveness of the best option is easy to identify. On the contrary, when the interattribute correlation is negative, the high utility of an alternative in terms of one attribute is outshined by the low performance in another, increasing the trade-offs that consumers have to undergo (Dhar 1996). In such cases, consumers need to put more cognitive effort to make these trade-offs in order to decide whether the positive features of an option can outweigh the negative attributes. The greater the degree of conflict in a choice is, the greater is the uncertainty in judging its overall utility (Fischer, Luce, and Jia 2000). For consumers, making trade-offs means engaging in more effortful and cognitively complex strategies and as a result the total time for decision is increased (Johnson and Meyer 1989; Klein and Yadav 1989; Payne, Bettman, and Johnson 1993). Therefore we expect that more positive interattribute correlation of a choice set negatively influences the choice set level inspection time.

The second component of choice complexity is the dispersion of the alternatives' attributes, which measures the degree of similarity of the alternatives. It is expected that if there are obvious differences among the alternatives in the choice set, the choice is easier since it is easy to distinguish the best option based on the attribute importance weight assigned by each individual. The choice complexity increases when the difference in terms of perceived utility between the alternatives is small (DeShazo and Fermo 2002; Shugan 1980). In a dominated choice set, there is little uncertainty and conflict. The closer the alternatives are in terms of their attributes, the more conflict a choice evokes, and the more effort is required by the decision maker (Bockenholt et al. 1991; Fasolo et al. 2009; Tyebjee 1979). In a choice set that lacks dominating options, the choice becomes more time demanding. The reason is that in low dispersion environments, more attributes must be considered to try to make an accurate choice, and the mental calculations are therefore harder (Bettman, Johnson and Luce 1993). Slow response times point to complex decisions in which the alternatives are equally attractive (Otter, Allenby and Van Zandt 2008). Also, in a choice set with close products (based on their attributes), it is more difficult to justify the choice of any particular option (Sela, Berger, and Liu 2009). Therefore, we expect that higher attribute range in the choice set decreases the choice set level inspection time consumers spend.

In general, consumers are sensitive to time costs. Therefore, they take into account the time it takes to reach a decision and in case it takes too long, they may decide to defer the decision (Fasolo et al. 2009; Jessup et al. 2009). Consumers have an implicit time threshold allocated in a given search task. If the time needed to make a decision surpasses this threshold, then the expected cost of searching is higher than the expected benefits of a more deliberated choice. As a result, consumers may decide to defer the choice (Fasolo et al. 2009). The implicit threshold depends on the type and importance of the decision. The decision maker may give up or postpone choice if an attempt to find the best option fails. In such a case, a feeling of confusion appears and may lead to unwillingness to commit to a choice (Dhar 1997). The confusion experienced can elicit negative emotions (Luce, Payne and Bettman 1999) and therefore lower conversion rates. Also, when the choice is taking too long, it shows that there is no strong preference for one of the options and the conversion likelihood decreases. Alternatively, when a fast choice is made, it signifies a strong preference for the selected alternative (Aaker et al. 1980).

Therefore, we expect that greater choice set level inspection time decreases the probability of website conversion. The underlying reason for that negative effect is that higher choice set level inspection time is driven by higher choice set complexity experienced by consumers. Choice complexity is expressed in terms of interattribute correlation of the alternatives as well as the attribute distance among the alternatives of the choice set.

Other Time Components

Besides product inspection and choice set inspection time, consumer online decision time can also be determined by other activities not included in the aforementioned aspects. We control for these alternative time uses by including a "other time" component. This time component captures for example the time spent on the web interface to request for information (Ozanne, Brucks and Grewal 1992). Consumers, who desire to receive product recommendations from an online firm, typically have to make a query regarding the specifications of the products they would like to purchase. Therefore, prior to accessing the choice set offered, consumers need to spend time to explicitly fill out a request communicating their own personal details or preferences. In past studies, the time spent on this part of a task was treated as query or input time and is not expected to substantially vary across consumers since it is a part of the process common to all consumers (Pollay 1970; Stone 1960). In addition, consumers may visit other pages on the recommendation site that present auxiliary information (e.g., general product category information). Variations in these uses of time may be attributed to higher involvement and hence would be expected to have a positive effect on conversion. Finally, download time may also be required. This is expected to be similar across consumers, since most online consumers in North America or Western Europe has access to fast internet connections (Bucklin and Sismeiro 2003).

4.3. Empirical Analysis

4.3.1. The Data Set

The availability of clickstream data has facilitated the ability to trail the actual behavioral paths of consumers when visiting a website (Bucklin and Sismeiro 2003). For the purpose of our study, we used disaggregate clickstream data from a leading recommendation website which provides information about financial products in the Netherlands[19]. The online company serves as an intermediary between consumers and

[19] Visitors can get recommendations for financial products provided from various banks, based on their self-filled data or inquiry.

financial institutions. The product category used in this study is house mortgages. The specific product category is a representative example of a search and durable product. Search and durable products are more complex and are expected to involve higher deliberation before final choice (Huang, Lurie, and Mitra 2009). Therefore, the chances of impulsive buying behavior (which may differently influence time spent) are minimized. The website allows users to find information about mortgages offered by various financial institutions (mostly banks) based on the configuration of their request. After completing their request, users face ten products in the main page and by clicking on the products they can inspect more information about the selected option (including additional attributes and extensive reviews). If they find a product (or even multiple products) that satisfies their needs, they can make a request for an offer through the website (in such a case the website communicates this request to the provider of the chosen product). Visitors complete the remainder of the transaction in direct communication with the mortgage provider. In addition, users can access some more general information about mortgages as well as information about specific local consultants regarding mortgage products.

The dataset consists of all visits to the mortgage section of the website during June and July 2010. The structure of the available data consists of all the requests and information exchanged between the user and the website within a given website session. For each session we recorded the user's individual characteristics, the choice set characteristics and a series of time stamped sequential decisions of the visitors on the website (in the form of unique URL's accessed).

4.3.2 Data Screening

Clickstream data contain very detailed and extensive records regarding each individual's behavior within a website. Despite the richness of the information companies possess, these datasets are often difficult to clear out and require an extensive data cleaning process. The total number of unique users within the dataset identified by a unique cookie ID and session ID was 24128. In the process of data cleaning, the first step was to eliminate the sessions which did not include the choice set page. These visitors aborted their task in the introduction phase where they were asked to formulate their mortgage specifications or they were browsing in the general information section without requesting for product information (approximately 35%). A typical problem of online providers is the high bounce rate (visits consisting of only one page). The reason is that in order to be considered as a potential for conversion, a user has to first fill in some personal information and some product specifications. Based on a cookie identification as well as IP address information we could control for repeated visits.

An additional option that users had in the website was to request for additional products moving further to a new page with an additional choice set comprised of more expensive products since the ranking is based on the interest rate of the mortgage (with least expensive products found in the first page). However, only 3.2% of visitors went further than the first page of each choice set (including the first 10 products based on their query specifications). Also, users could make a request based on a brand specification. Due to the availability and the logging procedure of the information, in such cases we were accessing only the inspected or requested product and as a result, the effects would be biased due to the large differences of price related factors (since the products were presented based on interest rates). Therefore, we only took into consideration the sessions that included only one choice set. As a result, we excluded those visitors that requested multiple choice sets (under different specifications such as different mortgage periods) (24% of the initial dataset). The final number of individuals included in our data set was 9473 (40% of initial pool).

Clickstream data is a rich source of information but can also be very noisy. Especially in the case of time measures, there is no way of examining the actual setting and behavior of the users. It is therefore necessary to impose some lower and upper limits regarding what can be considered as acceptable and normal behavior. Research in response times has shown that overly quick response times show lack of deliberation and long response times may be an indication that the user is not involved in the specific task (Otter, Allenby and Van Zandt 2008). For example, a user may quickly go through the website just to understand the process before thoroughly investigating its offers. On another perspective, a user may have left the webpage open without any action because he left the computer or is focusing on another webpage or computing task. For the lower threshold, we set a limit of 15 seconds spent in the choice set page (choice set inspection time) and excluded the users that did not pass that threshold (approximately 2% of total users). The excluded visits were mostly cases of very low involvement in the process and not speed or easiness of the choice (since there was no higher time duration in other pages either)[20]. Regarding the upper limit, we excluded sessions with duration higher than 30 minutes (Bucklin and Sismeiro 2003; Catledge and Pitkow

[20] The excluded sessions were not informative and refer to cases where visitors left the website at the next click.

1995). These cases (less than 0.1%) are mostly cases that remained inactive after a point, assuming that the visitors did not focus on the specific task.

4.3.3 Measures

The dependent variable of our study is website conversion. The main predictors we included in our model are the time measures during a given website session. In addition, to further strengthen our understanding of the underlying drivers of the expected relationships, we included some directly observable indicators of product attractiveness and choice difficulty in our analyses.

Website Conversion: After comparing (at the choice set level) and/or inspecting (at the product level) the recommended products, consumers make a decision regarding whether and what to purchase. If they are satisfied with an option, they can make a request through the website. If they are not satisfied with the website's offers, they can just leave the website without buying a product. We assume that, from the website's point of view, conversion is achieved when the consumer is requesting a proposal for a mortgage offer. The reason is that the revenue model of the company is based on both leads and closed deals. However, since the company did not provide data on follow up sales (also it is out of the company's influence), we focus on the leads model. We measure website conversion at a product level as a series of binary decisions of whether a user i requests an offer for a product j from a choice set. Whether the user made a transaction with the mortgage provider or not is not a focal point of this research for two reasons. First, the website in study does not have any control or authority on the consumer – firm interaction in further steps and therefore in that context is out of its jurisdiction. Second, completing a transaction depends on the mortgage provider and is something that cannot be influenced by the website in focus. Since the structure of the data is in the form of repeated measures at a product level for each choice set, we can also capture no choice option when none of the products in the set were ordered.

Time measures: Time was measured as the time difference in seconds between two consecutive page requests within a given session (Bucklin and Sismeiro 2003). Since each page contains an identifiable URL, it is possible to disentangle the time spent according to the nature of each page. The time spent in the page where the choice set is presented to the users (choice set level inspection time) is coded as choice inspection time. In that step, the user is facing all options from the choice set. Even though he can see some basic information (interest rate, brand and quality measures) about each alternative, we expect that in that page, the user is deliberating regarding what to inspect or even order. Choice inspection time is the amount of time the decision-maker takes to make a decision. Even though some form of product specific inspection can be realized in that page, we expect that this is allocated evenly across alternatives (including an order effect to control for an uneven allocation of time in that page). The choice inspection time is measured at the choice set level. When users decide which alternative(s) to inspect, by clicking on it, they can access a new page with more thorough information about the chosen product. The time spent in such a page is product specific and is regarded as product inspection time. In such a stage the user can decide whether to go back to the choice set page, order the inspected product or end the session. Note that an order can be realized even without inspection (directly from the choice set inspection page). Therefore, product inspection time shows real interest towards the product and is not just a necessary process step for the users. The time spent filling the specifications and personal information was coded as introduction time. In addition, any other type of time (i.e. fill in personal information, page loading, additional information pages) is classified as "Other Time" and even though is not a focal point of the study, it is used as a control measure.

A typical problem of clickstream data is that the duration of the last page view of each session is not known. The reason is that the website cannot record when a user moved to another site or closed the browser. Since our purpose is not the total session duration on the website but to analyze the impact of specific types of time, we did not take into consideration the last step of each session. The only exception was when the last step was a request for an order. In this case we recorded the request as a conversion.

All measures of time were log-transformed in order to reduce right skewness (Greene 2003). After doing so, the distribution of ln(*time*) closely followed a normal distribution (see Appendix of the chapter for an illustration of the distribution of time spent). To overcome the fact that because some products are not inspected and therefore the log of their inspection time (of zero seconds) cannot be taken, we added one second before using the logarithm to each observed time (Bucklin and Sismeiro 2003). We repeated the same approach for every time measure. In such a way we just shifted all time measures and therefore the estimation is not affected.

Product Attractiveness: In order to measure the attractiveness of each product, we take into consideration its distinctive attributes. The interest rate of the mortgage (Rate_{ij}) is similar to a price attribute where a lower rate increases the attractiveness of an alternative. We also control for some product specifications requested by the users such as period or the amount of the mortgage. In that way, the effect of higher interest rates at a choice set level is captured by these variables and therefore we could examine the effect of rate within a set. The quality measure of each product is captured by two distinctive measures. The first one ($Quality_{ij}$) reflects the ratings given by the website and is coded as a continuous variable from 1 to 5 (quality stars). The second approach is reflecting the ratings given by already existing clients ($Client_{ij}$) in a scale between 0 and 10 (however ratings ranged from 5.9 to 7.4). Some vendors miss the client ratings because of insufficient reviews (the number of needed reviews before this figure appears is not given from the company). In such cases, a dummy variable indicating existence of a client rating is taking the value of zero.

Choice Complexity: Choice complexity was measured at a set level since it reflects the conflicts and the distances between all alternatives in the choice set. Interattribute Correlation ($AttCor_i$) was measured as the average interattribute correlation between interest rate, and the 2 quality measures. The values of correlation between interest rate were reversed and as a result, positive values of $AttCor_i$ show choice sets that do not involve large trade-offs among the attributes of the alternatives (ranges from -1 to 1). In order to measure the dispersion within the choice set we measured the range of interest rate and quality values in the set ($DispR_i$, $DispQ_i$, $DispC_i$ respectively) as well as the number of different brands in the choice set ($NrBrands_i$).

Additional Control Variables: In addition to the main predictors, we also controlled for a series of independent variables that may influence the final outcome. The choice of the control variables was mainly driven by data availability. First, we measured some of the individuals' characteristics based on their application request. We measured their income (as well as partner's existence and income), the amount of the mortgage requested as well as the duration of the requested mortgage (in years). Also, we measured the time of the day when session started (to control for the fact that people spend their time differently when they are at work or at home in the evening). Finally, we measured the current bank provider of the individual (to control for loyalty effect towards the current bank). In terms of product characteristics, we measured whether the product is offered by the current bank of the individual. Also, we measure the position of the product within the choice set, in order to control for a possible order effect. Based on the order effect, products positioned higher in the product lists, are found to be perceived as more attractive and more often chosen (Xu and Kim 2008).

4.3.4 Empirical models

Effects of decision time on conversion

We model a visitor's decision to request a quote for a specific mortgage product. Our model predicts the probability of product conversion within a given session the website, given that the visitor has accessed a choice set. We use a binary logit model at the product level. In order to control for unobserved heterogeneity, we allow for a user-specific random intercept (β_{0i}) that captures any idiosyncrasies an individual may demonstrate in performing an order in the website. For the explanatory variables, the effects are fixed across individuals. Therefore the probability that individual i requests a quote for product j ($Conv_{ij}$) in from a given set is a function of the logarithms of the set specific choice set level inspection time ($ChoiceInspTime_i$) and Other Time ($OtherTime_i$) as well as of the product level inspection time ($ProdInspTime_{ij}$). We also included a dummy for product inspection, the position of the product as well as some control variables (such as personal and query specifications).

$$(1)\ Conv_{ij} = \beta_0 + \beta_{0i} + \beta_1\ ChoiceInspTime_i + \beta_2\ ProdInspTime_{ij} + \beta_3\ OtherTime_i + \beta_4\ InspDummy_{ij} + \beta_5\ Position_{ij} + \beta_6\ Amount_i + \beta_7\ Income_i + \varepsilon_{ij}$$

The error term ε_{ij} in is assumed to follow an i.i.d. logistic distribution. The random error term β_{0i} is i.i.d. $N(0,\sigma^2)$.

Drivers of Product Level Inspection Time

We model the log of product level inspection time spent for a specific product ($ProdInspTime_{ij}$) as a function of product specific covariates. We jointly model the inspection-request (InspDummy) and page-view duration (*ProdInspTime*) decisions with a type II Tobit model (Heckman 1978). Such a model is applicable in this type of log-file duration data. We therefore control for a possible selectivity bias in page-view duration (Bucklin and Sismeiro 2003). We expect that the main driver of the positive role of product level inspection time on conversion is the level of product attractiveness. In the case of page view durations, a normal linear model would be inappropriate because it allows for negative duration predictions even though all page-view durations are non-negative. Besides the interest rate, the quality measures as well as brand dummies of the most popular providers which capture the product attractiveness, we also controlled for the order of the product, and whether the product is offered from the current bank provider of the visitor. We also included some control variables regarding personal (such as the income of the respondent and his partner, the time of the day of the session) and product specification variables (such as the amount of mortgage, the period).

$$(2)\ ProdInspTime_{ij} = \begin{cases} ProdInspTime_{ij} & if\ ProdInspTime_{ij} > 0 \\ 0 & if\ ProdInspTime_{ij} \leq 0 \end{cases}$$

(3) $\text{ProdInspTime}_{ij} = \gamma_0 + \gamma_2 \text{Rate}_{ij} + \gamma_3 \text{ Quality}_{ij} + \gamma_4 \text{ Client}_{ij} + \gamma_5 \text{ CDummy}_{ij} + \gamma_6 \text{ Period}_i + \gamma_7 \text{ Position}_{ij} + \gamma_7 \text{ Current}_{ij} + \gamma_D \text{ BrandDummies}_{ij} + \gamma_C \text{ ControlVariables}_i + \nu_{ij}, \nu_{ij} \sim N(0, \sigma^2)$

Drivers of Choice Set Level Inspection Time

We also model the log of choice set level inspection time ($ChoiceInspTime_i$) spent within a session as a function of set specific choice complexity covariates (interattribute correlation and dispersion) since we expect that choice complexity is the main driver of choice set inspection time. Since we imposed a restriction for visitors who spent less than 15 seconds in choice set level inspection time, we use a linear regression model. We include (similarly to the previous models) some control variables in the model.

(4) $ChoiceInspTime_i = \lambda_0 + \lambda_1 \text{AttCor}_i + \lambda_2 \text{DispR}_i + \lambda_3 \text{ DispQ}_i + \lambda_4 \text{DispC}_i + \lambda_5 \text{NrBrands}_i + \lambda_C \text{ ControlVariables}_i + \zeta_i, \zeta_i \sim N(0, \sigma^2)$.

4.4. Data Analysis and Results

4.4.1 Descriptive Statistics

The following table shows descriptive statistics of selected variables from the dataset. In total, 8.2% of all products presented to users in our dataset were inspected. Also a 3.8% of all products presented were ordered. However this percentage increases to almost 23% of the products that were inspected[21]. At a set level, in 30% of the sessions there was an order whereas in 44.7% of the session there was an inspection of at least one product. In cases of an inspection, in most of the cases only one product was inspected (84%). On average the mortgage loan visitor had an annual gross income of €49.459 and desired a mortgage loan of €231.596. These numbers largely correspond with the total mortgage market in the Netherlands. In the following table, the average behavioral patterns are illustrated.

[21] There were almost 1.9% of all products that were ordered without being inspected.

4.4.2 Effects on Website Conversion

Product Level Inspection Time. The coefficient of product level inspection time of a product has a significant and positive effect on the probability of conversion of the inspected product. Even when controlling for the random individual specific effects, the effect is positive. This result confirms our expectation that spending more time inspecting a product increases the chances that the inspected product is ordered. Even when we control for the effect of number of inspected products or whether a product was inspected at the set level (practically that means that another product was inspected), the effect remained positive and significant showing that inspection time increases the chance that the consumer will convert to the website. Finally, inspection of another product decreases the chances that the focal product is chosen.

Table 4.1. Descriptive statistics

Variables	Mean	Median	Min	Max.
Product Level Inspection Time*	73	34	6	1721
Choice Set Level Inspection Time*	137	71	15	1799
Total Inspection Time*	332	297	49	3595
Other Time*	76	36	0	1896
Number of Inspected Products	1.24	1	0	9
Number of Brands in a choice set	8.02	8	3	9
Interattribute Correlation	-0.05	-0.09	-0.55	0.62

*Time measures are in seconds

Choice Set Level Inspection Time. The coefficient of choice set level inspection time of a product has a significant and negative effect on the probability of conversion in the website. This result confirms the proposition that spending more time comparing the alternatives decreases the probability that a product is ordered. However, when we control for the number of inspected products, this effect becomes insignificant.

We tested for alternative page-view-duration model formulations (actual time in seconds, percentage of total time) but the use of logarithm in the time variables outperformed the rest in terms of model fit. We compared the proposed model with a model where decision time is treated as one-dimensional. In the latter model, total decision time has a significant positive effect on conversion. This shows that more time on aggregate can work as an advantage for the online provider. The model fit of our proposed model outperforms the latter model in terms of McFadden ρ^2 as well as in terms of improvement in the log likelihood and information criteria (AIC, BIC). Therefore, we conclude that whereas total decision time is a good indicator of involvement of the individuals, it can be more insightful to see how individuals allocate their time across different pages of the website within a session.

Table 4.2. Results on Website Conversion			
Random Intercept Logit model / Dependent Variable: Conversion$_{ij}$			
Independent Variables	*Model with one dimensional time*	*Model with Time Dimensions*	*Model with Time Dimensions(2)*
Intercept	-2.98**	-3.72**	-3.62**
Random Intercept (β_{0i})	0.96**	0.97**	0.91**
Total Decision Time	0.15**		
Choice Set Inspection Time		-0.06*	-0.01
Product Level Inspection Time		0.20**	0.12**
Other Time		0.34**	0.32**
Inspection Dummy$_i$	2.37**	1.71**	2.73**
Position in the Choice Set	-0.37**	-0.38**	-0.35**
Current Provider	1.47**	1.47**	1.42**
Amount of Mortgage	-0.24**	-0.01	-0.00
Income	-0.14**	-0.12**	-0.12**
Period	-0.01	-0.01	-0.02
Nr of Inspected Products			-0.64**
McFadden's ρ^2	0.21	0.22	0.24
Log Likelihood	-10568	-10382	-10241
AIC	20929	20785	20506
Signif. Codes: '**' 0.01 '*' 0.05			

4.4.3 Drivers of Product Level Inspection Time

We further investigated whether our assumption for the main underlying driver of the positive effect of product level inspection time on conversion is true. We expect that product level inspection time is driven by the level of product attractiveness of the alternatives. As measures of product attractiveness, we used the interest rate of the products expecting that higher interest rates decrease the attractiveness of a product. Also, we used two sources to measure quality; one from the website provider (Quality) and one from other visitors of the website (Client) expecting them to have a positive relation to attractiveness. In addition, we used brand dummies for the most popular and frequent mortgage providers as well as a dummy for the current bank provider of the visitor. On average, the interest rate of the mortgages was 4.44% and the quality ratings of the website and the clients were 2.54 (out of

5) and 6.48 (out of 10) respectively.

Using a Tobit type-II model, we estimated the effects of product attributes on the inspection decision as well as on the inspection duration given the inspection occurrence. Most of the effects on the Probit selection model were significant. More precisely, the effect of interest rate on inspection selection was negative, showing that users tend to select for inspection products with lower prices. Regarding the quality measures, both Quality and Client ratings have positive and significant effects on inspection decision[22]. Users select to inspect products that have higher quality ratings. We also controlled for some brand dummies (taking into account only the major brands that appear in more than 5% of the cases), which also showed significant influence on inspection decision. Finally, consumers choose more to inspect products that appear high in the list (even controlling for the net price effect based on which products are ranked) as well as products offered from their current bank.

In the second part of type II Tobit model, the outcome equation showed the effects of product attributes on inspection duration conditional on the inspection occurrence. The effect of interest rate on inspection duration was negative, showing that users inspect for less time the more expensive products. Client ratings have a positive and significant effect on product level inspection time[23]. Users spend more time inspecting products that have higher client ratings. The brand effects in most cases were not significant, showing that a brand influence holds for the inspection selection but not for the duration of the inspection. The order effect significantly holds for inspection duration as well. Visitors invest more time inspecting products that are placed higher in the list. No demographic or product query (amount, period of mortgage) variables showed any significant effects.

In order to strengthen our expectations about the main driver of product level inspection time, we also performed an additional analysis including the measures of choice difficulty. By including these additional predictors, we wanted to examine whether inspection times are also influenced by choice complexity and also whether by controlling for the choice complexity, the effect of product attractiveness remains unchanged. Based on the analysis, choice difficulty influences the inspection selection but less the product level inspection duration decision. More specifically, interattribute correlation negatively influences inspection selection. Less complex choice sets lead to less inspection. The price

[22] The net effect of Client Ratings is positive since Client Rates range from 5.9-7.3. Therefore, the minimum effect is 2.00-7.3*0.25=0.175.
[23] The net effect of Client Ratings is positive since Client Rates range from 5.9-7.3. Therefore, the minimum effect is 7.3*0.43-2.41=0.127.

dispersion increases both inspection selection and duration, probably due to the higher amount of money at stake. Quality ratings dispersion has a positive effect on inspection decision. This may be attributed in the fact that since the total range is relatively small (quality rates were 2 or 3 in 95% of the cases). The direction and significance of the product attractiveness effects remained unchanged.

Table 4.3. Product Inspection Time Model

Dependent Variable	**Inspection Dummy**	**Inspection Time**	**Inspection Dummy**	**Inspection Time**
	Product Attractiveness	*Product Attractiveness*	*Product Attractiveness and Choice Complexity*	*Product Attractiveness and Choice Complexity*
Independent Variables	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*
Intercept	-0.67**	2.35**	-0.74**	1.64**
Rate	-0.03**	-0.10**	-0.08**	-0.18**
Quality	0.05**	-0.06	0.06*	-0.06
Client	-0.25**	0.35**	-0.19**	0.40**
Cdummy	2.00**	-1.81*	1.58**	-2.18**
Current	0.38**	0.10	0.38**	0.12
Position	-0.20**	-0.12**	-0.20**	-0.12**
Brand A (Allianz)	-0.42**	-0.03	-0.39**	-0.00
Brand B (REAAL)	-0.07**	-0.23*	-0.06**	-0.21**
Brand C (ABN)	0.31**	-0.05	0.37**	0.07
Brand D (Fortis)	-0.29**	0.04	-0.24**	0.07
Brand E (MoneYou)	0.25**	0.08	0.23**	0.08
Brand F (BNP)	-0.44**	-0.39**	-0.48**	-0.49**
Brand G (Hypotrust)	-0.25**	-0.34**	-0.20**	-0.32**
Brand H (Delta)	-0.34**	-0.02	-0.27**	0.04
Brand I (SNS)	0.11**	-0.01	0.20**	0.10
Attribute Correlation	-	-	-0.15**	-0.19
Dispersion Rate	-	-	0.51**	0.73**
Dispersion Quality	-	-	0.08**	0.05
Dispersion Client	-	-	0.07	0.19
Number of Brands	-	-	-0.00	0.07**
LogLik / Sigma / Rho	-47056.91 / 1.93** / 0.26*		-46967.42 / 1.95** / 0.30**	

[a] A list of dummies related to the most frequent mortgage providers (brands) in our dataset.

4.4.4 Drivers of Choice Set Level Inspection Time

We performed a third analysis in order to investigate the drivers of choice set level inspection time. We expect that choice set level inspection time is driven by the degree of choice set complexity. As measures of choice complexity, we used the interattribute correlation and the dispersion of the attributes within the choice set. All these measures are captured at the set level. On average, the interattribute correlation within a choice set is -.05. In addition, the average interest rate, quality and client rating dispersion measures are .23, .95 and 1.15 respectively. Finally, we also used the number of different brands within the choice set as an additional measure of dispersion. The restrictions in our dataset regarding choice set level inspection time (lower limit was 15 second), result in no censorship within our dataset (so a Tobit model does not apply here). The results of the linear regression model show a negative and significant effect of interattribute correlation. Therefore, the higher and positive the interattribute correlation is, the less time users spend compare the alternatives. The reason is that when the interattribute correlation is positive, the choice is easier and therefore, users do not need much time to make a decision. Regarding the dispersion measures, the effects of both quality measures dispersion is negative. This is in line with our expectation that higher attribute dispersion will decrease the choice set inspection time in the website. The underlying reason is that a larger range makes the options more distinguishable and also the choice easier. The effect of number of different brands is positive, opposite to our expectations. However, this effect signifies the fact that when there is more variety, consumers need more time to decide.

Table 4.4 Choice Set Inspection Time Model

Dependent Variable: Choice Set Inspection Time		
	Choice Difficulty	*Choice Difficulty and Attractiveness*
Independent Variables	Coeff.	Coeff.
Intercept	3.72**	5.81**
AttCorr	-0.15**	-0.19**
DispR	0.03	0.14**
DispQ	-0.12**	-0.16
DispC	-0.11**	-0.12
NrBrands	0.11**	-0.11**
Current Bank Included	-0.05**	-0.04**
Rate[a]	-	-0.12**
Quality[a]	-	-0.04
Client[a]	-	-0.24*
R^2	0.02	0.02

a. Minimum values in the choice set

We performed an additional analysis including the measures of product attractiveness.

By including these additional predictors, we wanted to examine whether choice set level inspection time is also influenced by the attractiveness of the products' attributes as well as whether by controlling for the added predictors, the effect of choice difficulty remains unchanged. The results indicate that when controlling for product attractiveness, the effects of choice difficulty are only slightly affected. Regarding the additional predictors, the price related measure has a negative significant effect on choice set inspection time. The explanation is that when the choice set includes expensive alternatives, individuals spend less time because the potential of finding a very good product is decreased. Therefore, they may skip the current choice set and respecify their request. The same effect appears for Client ratings. The negative effect indicates that when a choice set has high client ratings, the attractiveness of the choice set leads to more product level inspection of the alternatives and therefore, less choice set level inspection time.

4.4.5 Robustness checks

We performed some additional analyses in order to increase the robustness of our results. First we checked the direct effects of product attractiveness and choice complexity on product conversion probability and whether these effects are mediated by the decision time dimensions of our model. Based on two logit models, first we tested whether product attractiveness influences product conversion and subsequently whether by including the time measures, these effects still hold. We also incorporated a random intercept to capture the individual specific effects that are not captured by the covariates of the model. Based on this analysis, product attractiveness attributes positively influence product conversion probability. Additionally, choice complexity negatively influences product conversion probability since interattribute correlation and dispersion measures have positive effects on conversion. Therefore, the easier the choice and the higher the difference between the alternatives, the higher the chances of conversion are. However, when we include the time measures, the effects of product attractiveness become weaker showing partial mediation (except the effect of client ratings which is disappeared, therefore leading to full mediation). Also, when we include the time measures, the effect of interattribute correlation disappears showing full mediation. Regarding the dispersion measures, by including the time measures, the effects are becoming weaker, showing partial mediation. This mediation analysis is evidence against the endogeneity of the time measures.

We also used squared values of complexity, since if a choice set is too complex, users may use simplifying heuristics to decide. In order to confront the negative interattribute correlation of a choice set, consumer have to engage in compensatory decision rules given that they good features of the chosen alternative compensates for the bad (Johnson and Meyer 1989). In a buying environment characterized by negative interattribute correlation, consumers assign weights in each attribute defining in that way their relative importance, and the decision outcome is based on these ratings (Häubl and Murray 2003). However, the effects of the squared values were not significant.

Moreover, the squared values of time were also tested in order to examine whether time has an inverted-U shaped effect based on the idea that consumers get tired after spending a lot of time on a task. We found a significant positive effect of product level inspection time (1.207) and a negative effect for the squared value of product level inspection time (-.123). Practically that means that the effect starts decreasing after an inspection of approximately 170 seconds. For choice set level inspection time, the effect of the squared value was positive and significant (whereas the linear effect was negative and significant). However, based on the boundaries we set for choice set level inspection time, the effect is always negative, but almost stable after approximately 365 seconds.

Finally, we examined whether there is an unobserved factor that may influence both product and choice set level inspection time. The correlation between product and choice set level inspection time is -0.02, indicating that these two constructs are not following the same patterns. Additionally, we included the choice set level inspection time in the product level inspection time model in order to control for whether the effects of product attractiveness remains stable. The result showed no difference in the effects of the predictors of product level inspection time, though choice set level inspection time was significant and positive (showing some average increased time spent across pages within a session).

4.4.6 Implications for composition of the recommended set

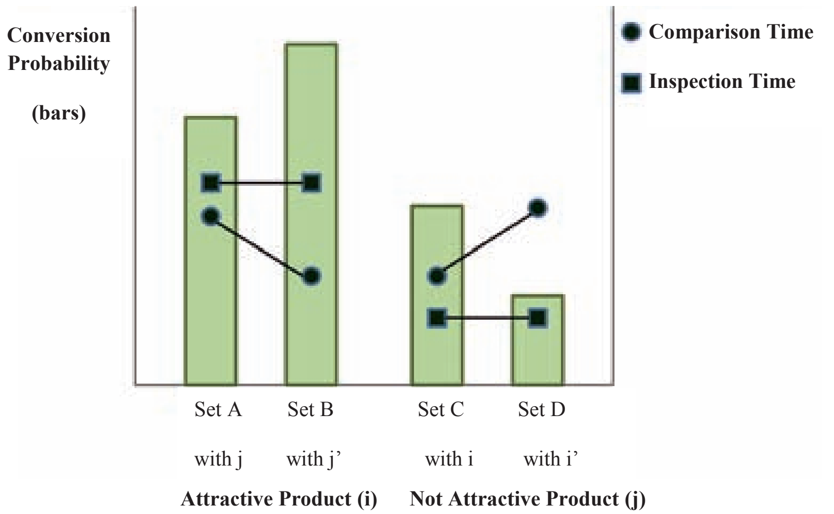
Based on the results of our models, we performed a simulation in order to illustrate the practical effects of time on product conversion. We show that for the same choice set level inspection time, spending more time inspecting a product increases its probability of conversion, whereas for the same product level inspection time, if more choice set level inspection time is needed, that may harm the chance of ordering a product from the website.

Table 4.5. Time Allocations and Conversion Probability				
		Product Level Inspection Time (in seconds)		
		50	100	150
Choice Set Level Inspection Time (in seconds)	50	0.18	0.23	0.25
	100	0.16	0.20	0.22
	150	0.15	0.19	0.21

In addition, we show how conversion probability for product i can be altered, if we add an equally good and attractive product, in comparison to when we add a less attractive product. The probability of conversion for a product i is higher when it is included in a choice set B with an inferior product j', compared to a choice set with an equally attractive product j (set A). The reason is that in the first case the choice set level inspection time is less because the differences between the products are clear and large. Also the product level inspection time remains the same. Therefore, although online sellers always try to satisfy their consumers, by including the best alternatives, we show that that is not necessarily the best option. It is more preferable to also include less attractive products in a choice set, because then the choice set level inspection time decreases. Moreover, the opposite effects appear when the focal product is not the best option in terms of attractiveness. Although the chances of conversion are low, due to the low attractiveness of the product, these chances are even decreasing when it is paired with an equally inferior product (set D compared to Set C). The reason is that the differences are not so distinctive and therefore the complexity of the choice increases.

Finally, we examined what happens in terms of average probability of conversion when we replace the last product of the choice set with a standard product of lower attractiveness in terms of benefits. Based on a simulation we performed, we found that in such a case, the average probability of website conversion increases in 90% of the cases by an average increase of approximately 100% (2.1% versus 4.5%). Also, we checked the hit rate of ordered products, by comparing the effects from a choice set composition model (attractiveness and complexity on conversion) to the time measures model. Although the hit rate (ordered products had the two highest predicted probabilities of order) was the same (approximately 49%), combining both predictions result in a predicted hit rate of 56%. However, the time model has a higher hit rate for products ordered lower in the product list (25% vs. 20%).

Figure 4.2. Conversion probability and Choice Set Composition



4.5. Discussion and Conclusion

4.5.1 Research Implications

This study investigates the different effects of time spent on a website across different sections of a visit. By using data from actual consumers' browsing behavior, we could directly examine how different time allocation choices influence the website conversion probability. Overall, this study aims at presenting a more complete way to understand the effects of website visit durations and also to propose an explanation for the debating finding in previous literature.

Whereas extant literature on decision time has showed contradictory findings regarding its effect on conversion probability, we present an alternative approach that can explain this conflict. Some studies showed that higher decision time leads to higher chances of conversion due to the increased probability that consumers find a better product and their decreased choice uncertainty (Bucklin and Sismeiro 2003; Danaher, Mullarkey, and Essegaier 2006; Otter, Allenby and Van Zandt 2008). Other studies showed that higher decision time represents higher consumer effort and opportunity cost and, leads to lower conversion (Berry 1979; Diehl 2005; Johnson, Bellman, and Lohse 2003). In this paper, we argue that decision time is not a one-dimensional construct but can rather be disentangled into further dimensions that can explain these oppositional indications. We disentangle total decision time spent on a shopping website into product and choice set level inspection time. We show that these two aspects have opposing effects on website conversion. Product level inspection time is the time consumers spend assessing information for a specific product whereas choice set level inspection time is the time spent by consumers for choosing which alternative to inspect or purchase. We show that spending more time comparing alternatives (at a choice set level) decreases the chances of conversion. The underlying reason is that choice set inspection time is an indication of the choice set complexity and of choice uncertainty which increases the risk associated with making a decision. In this way, we show when more time signifies higher engagement and when higher effort.

Second, we expect that spending time inspecting each given alternative increases the chance of conversion, because it represents a higher expected utility of searching for information on the alternative. We expect that whereas product level inspection time is the reason for the positive effect of time, the time spent comparing the alternatives (at the choice set level) negatively influences the conversion likelihood on the website. Therefore, we give an explanation for the diverse findings in the literature. This study enables us to provide a link between observed time allocation strategies and potential website conversion. The final choice of conversion is not merely explained by the total time spent on a website but rather by the allocation of the total decision time across the different types of time. Although the concept of time spent has a long tradition in marketing and economic literature (Jacoby, Szybillo and Berning 1976; Otter, Allenby and Van Zandt 2008), this is the first study that attempts such a decomposition of actual time spent on a website in order to predict website conversion.

In addition, we show that the main driver of product level inspection time is the product attractiveness of the choice set's alternatives. The better the products offered by a website, the higher the inspection time from the consumers. Therefore, we offer an explanation of the positive effect of product level inspection time on website conversion. Product level inspection time is higher for the alternatives that possess more beneficial characteristics. This is in line with marketing theories showing that more attractive products have higher chances of getting chosen. Also, we demonstrate that the underlying driver of choice set level inspection time is the level of choice complexity measured in terms of alternatives trade-offs and similarity. This suggests that the complexity of the choice hardens the task of the consumer and therefore this expected drawback is filtered through the increased choice set level inspection time which negatively influences website conversion.

Moreover, the use of real life clickstream data to support our propositions, though noisy, can give a more convincing support for the consistency of our findings. Whereas, an experimental approach might give a more controlled environment and more straightforward insights, the fact that even in a real behavior environment, our expectations hold, increases the magnitude of our findings.

Finally, an additional interesting finding is that there is a tradeoff between attractiveness and complexity in a choice set. Whereas normative theory would suggest that companies offer the best options to the consumers so that the probability of purchase incident increases, we show that offering multiple close alternatives (even though highly attractive) in a choice set increase the difficulty of consumers' choice. As a result, choice set level inspection time increases and therefore the online conversion chances may drop.

4.5.2 Managerial Implications

From a managerial perspective, this study spotlights some crucial issues for online companies. We present some implications of our findings for online companies. First, online firms can benefit from our findings to improve the composition of the offered product choice sets by taking into consideration the allocation of time spent by consumers on a given session and by balancing consumers' time at the product and choice set level. The attractiveness of a choice set as well as the complexity and difficulty of a choice are subjective and might differ across heterogeneous group of customers. Therefore, the same choice set may vary in terms of attractiveness across customers. Also the perceived difficulty of the choice may also differ across different visitors. Decision time and more specifically, the allocation of decision time across its proposed dimensions can offer a good process level validation of the subjective attractiveness and difficulty of a choice set. Companies can benefit by tracking the time allocation of their online visitors and outline their preferences and distinctive characteristics.

Second, by disentangling decision time, we improve the current web metric approach of total time on a website. Business web metrics measure "time on site" or "duration of a visit" as an indication of effective web traffic". We show that trying to increase the duration of a visit does not have the same effect in all the web pages. Website owners should attempt to increase duration in specific parts of the website and shift the time allocation in a given session towards product inspection parts.

Third, we show that there is a trade-off between choice set attractiveness and choice set difficulty. Whereas the traditional approach is to best serve the customer by offering the best alternatives available, we show that including a less attractive option (and decreasing attractiveness of the choice set), choice complexity is decreased as well. As a result, an easier choice has beneficial effects towards conversion. The distinctive components of decision time (product and choice set level inspection time) can serve as a good process level validation of the subjective attractiveness and complexity of a choice set. This is very important especially in the case of product intermediaries. These websites do not have control over the product attractiveness of what they can offer, but rather they can influence the composition and choice complexity of the offered choice sets. Therefore, the inclusion of more distant alternatives can increase the conversion probability in their website.

4.5.3 Conclusion

The use of real world-website data increases the validity of our findings, but also imposes some inherent restrictions on our analyses. First, it can be assumed that inspection of an alternative can be also performed in the product list webpage. In our approach, we consider the time spent on this page as choice set level inspection time that harms conversion. However, we are not able to control for the specific products which consumers elaborate on during their staying on the product list page. The use of an eye tracking mechanism could give us some insight but even in that case, we should not assume that focusing on a given product means that consumers are fully involved in inspecting it and not just comparing it with the rest of the listed products. Moreover, since many websites offer the option of inspecting multiple products at once, we consider that even in that case, the time spent in the case of many products inspecting is allocated in an isomeric manner.

Second, opposite to the above expectations, some researchers proposed that when respondents put more effort in evaluating a specific product, they are less likely to choose it (Garbarino and Edell 1997). This hypothesis is based on the negative affect possibly generated by increased effort towards some options. The cognitive load that might incur after too much information can confuse consumers and lead them to postpone or abort taking a decision (Guo 2001). This would lead to an inverted-U relationship between product level inspection time and conversion rate. However, we expect that within some typical time thresholds, cognitive load is not activated. Therefore, the reverse effects can only be met in extreme cases. Moreover, this reverse effect could be rooted on the type of information that consumers face under inspection. If the information is positive it may increase the purchase probability. Similarly, negative information may decrease the purchase probability. However, since inspection decision is driven by the attributes of the products, it is not usually expected that consumers end up with negative information about the inspected products. However, there is also some counterintuitive evidence about the relationship between product attributes and inspection effort. The inspection effort spent for a given product, which is measured by inspection time, is found to be higher for difficult to evaluate products (Garbarino and Edell 1997). Consequently, a product which is easy to evaluate and outweighs the rest of the options in terms of attributes would require less time. This is contrary to our expectations but can be explained by a possible pattern in the outliers of consumers' behavior. Even though the favorability of product attributes positively influence the inspection effort of consumers, when an alternative is clearly favorable compared to all other options (and therefore easy to evaluate), then the expected inspection effort might decrease.

In contrast, a greater similarity between choice alternatives (increasing the complexity in choice) can reduce search effort, due to lower expected benefits from additional search. According to that theory, in case all alternatives are close together in terms of their attributes, consumers may face lower choice uncertainty since all there are no substantial differences between options and as a result they stop searching (Niinivaara et al. 2008).

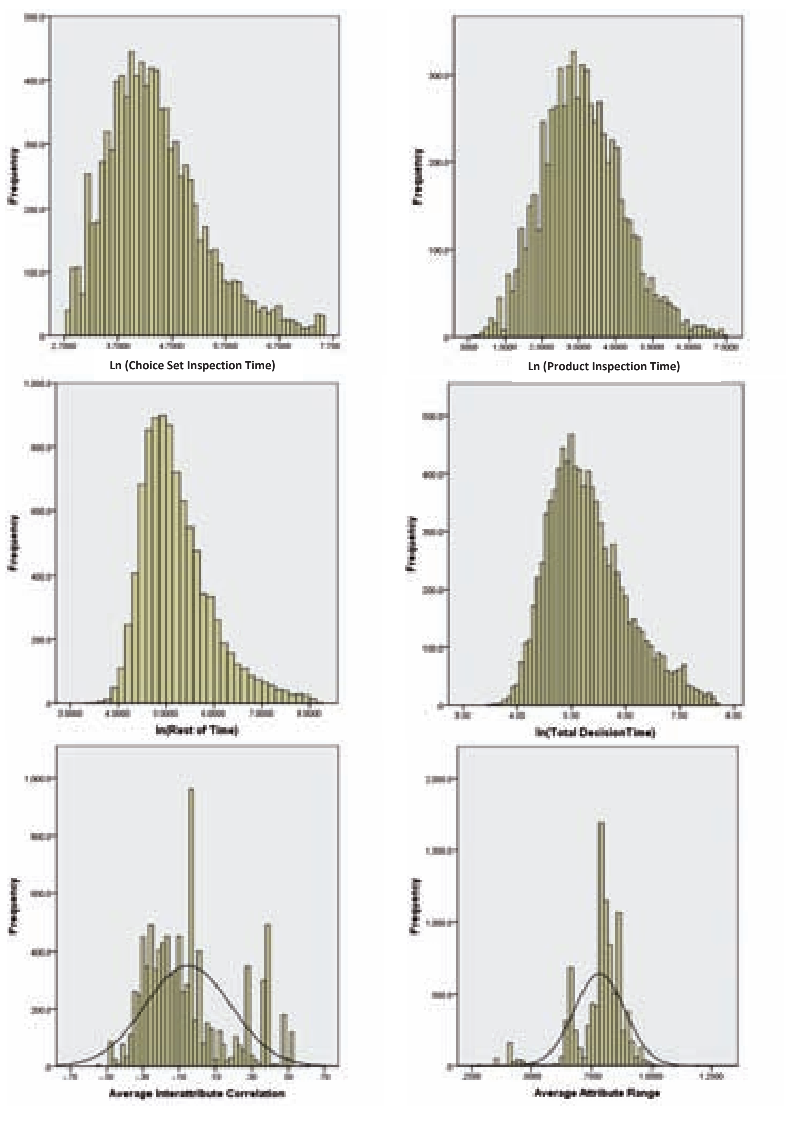
Additionally, information search patterns may differ based on the nature of the product searched (Huang, Lurie, and Mitra 2009). In our empirical application we used a complex and durable product. It would be interesting to see whether these findings apply also in different product categories.

Based on IP address information we could control for repeated visits. However, repeated visits were scarce within our dataset. We expect that the reason is that visitors that did not request an offer in their initial visit already got a good indication of the available products and could directly contact the mortgage providers instead of returning to the website (eliminating in such a way an intermediary). This is an additional indication of the importance of conversion in such websites, since usually these informational websites are receiving revenues by the placement of products which also depend on the amount of potential customers that contact the mortgage providers through the specific website.

In summary, the current work has investigated the effects of different dimensions of total decision time on online conversion. Disentangling decision time into product and choice set level inspection time, we show that the contradictory findings in the literature regarding the effects of time on conversion might be attributed to the opposite effects of the two dimensions proposed. Thus, it is very important to understand how consumers on a website allocate their time during a visit and what drives this allocation. We find that attractiveness of a choice set increase the expected utility of the choice and therefore increase product level inspection time. In parallel, increased complexity and difficulty of the choice set may lead to higher choice set level inspection time, which in turn decreases the chances of conversion. An improved understanding of how the composition of an offered choice set influences the allocation of time and how different time allocation decisions may lead to different behavioral outcomes affects the success and performance of the website and is critical for online firms. Therefore, the important question for websites is not how much time consumers spend on site but rather how consumers distribute this time to different pages and tasks.

Appendix of Chapter 4

Distribution Graphs of Time Measures



Εν οίδα ότι ουδέν οίδα
"All I know is that I know nothing"
Socrates (in Plato's Apology) (469 - 399 BC)

Chapter 5
Conclusion

The objective of this research was to improve the understanding of the role of consumer effort in online decision-making. The general context of this thesis focuses on decision-making in situations where a certain level of involvement is required in order to make informed decisions. By using cognitive components in explaining microeconomic behavior, we show that decreasing consumer effort (across different sources) does not necessarily lead to favourable results for online firms and that in some situations increasing consumer effort can be even beneficial for firms. By examining this counterintuitive role of consumer effort, both academic scholars and business practitioners can better understand consumer behavior but also improved ways of serving the customers. In this chapter, we will provide a summary of the main findings of the three empirical studies together with their academic and managerial implications. Finally, we will point out some avenues for future research.

5.1. Summary of Main Findings

In chapter 2, we investigated the effects of consumer effort in the context of content-based websites. Content-based websites are online providers that offer information. This offered information is their main value component (Huizingh 2000; Liu, Sarkar, and Sriskandarajah 2010) and constitutes the end product (i.e. news or health information websites). We showed that information in a content-based website can be offered in multiple ways that vary in the level of user effort they require. Using a distinction in operationalizing user effort exerted in these websites into information-based and interaction-based user effort, we showed that user effort is not always equally beneficial. Information-based user effort refers to the quantity of informational content and more focused and relevant informational content decreases consumer effort (Jacoby, Speller, and Berning 1974; Malhotra 1982). Interaction-based user effort refers to the process by which the informational content is generated. Consumers can either delegate the task to the system or actively perform the task themselves but exerting higher effort. Decreasing the required user effort in either dimension has the potential to substantially influence the quality of the outcome of consumers' information task (Häubl and Trifts 2000; Todd and Benbasat 1994). The way the information is communicated can directly influence the amount users learn about the informational content they receive in the website. However, this effect is not always positive. Whereas information-based user effort reduction increases content learning, interaction-based user effort reduction has the opposite effect on learning. In turn, content learning significantly influences users' website evaluation and user revisit intention and mediates the effectiveness of different information communication approaches that vary in terms of user effort required regarding these behavioral outcomes. Therefore, we showed that content learning can capture and explain the effectiveness of different sources of effort reduction regarding information acquisition in a content-based website even if it requires additional exerted user effort.

In chapter 3, we attempted to investigate the role of information absorption in a transactional setting. We introduced an additional source of consumer effort; the complexity of a choice set's composition. Consumer decision making is taking place in environments that invoke a certain degree of choice complexity and uncertainty. We showed in two empirical studies that increasing consumer effort by making a product choice set more complex can have beneficial effects. We presented a framework on how the composition of a recommendation choice set can influence consumer product knowledge. We proposed that choice set complexity increases objective consumer knowledge due to increased deliberation of the consumers whereas it decreases consumer confidence and hence, their subjective knowledge assessment. A more complex choice set implies a higher consumer effort required in order to generate a decision. However, the positive effect of complexity is overshadowed by the decreased consumers' confidence when choice sets become more complex. In addition, our results validated the managerial importance of consumer product knowledge in increasing the probability of purchase (increasing website conversion) as well as the willingness to pay for the chosen product. Moreover, we found evidence of the mediating role of objective knowledge between choice set complexity and subjective knowledge. Finally, we found a mediating effect of consumer product knowledge (both objective and subjective) on the relationship between choice set complexity and the consumers' behavioral responses.

In chapter 4, we introduced an additional source of consumer effort as an indication af the actual effort excerted in a website visit. We examined the role of time related consumer effort in the context of product recommendation website. Product recommendation websites are faced with contradictory research findings on whether to increase or decrease online inspection time. Some studies showed that higher decision time leads to higher chances of conversion due to the increased probability that consumers find a better product and their decreased choice uncertainty (Bucklin and Sismeiro 2003; Danaher, Mullarkey, and Essegaier 2006; Otter, Allenby and Van Zandt 2008). Other studies showed that higher decision time represents higher consumer effort and opportunity cost and, leads to lower conversion (Berry 1979; Diehl 2005; Johnson, Bellman and Lohse 2003). While greater online inspection time in a website increases the chances of conversion due to lowering consumer product uncertainty, it may also signify increased consumer effort and opportunity cost. In this study, we disentangled total consumer online inspection time into two components that showed opposing effects towards website conversion: choice set and product-level inspection time. At the product level, more inspection time is favorable since it reflects increased expected utility and is driven by the attractiveness of the recommended products. However, at the choice set level, increased inspection time has the opposite results since it determines the increased complexity of the recommended choice set (defined by the interattribute correlation and attribute range).

5.2. Academic Implications

In recent years, there is an increased interest in investigating the role of consumer effort within the context of user-website interaction (Bechwati and Xia 2003; Gretzel and Fesenmaier 2006; Liang, Lai, and Ku 2007). In the current dissertation, we investigate the different sources and facets of consumer effort and show that increased effort may even lead to favorable outcomes in some circumstances. In this context, the current dissertation contributes to this literature in a number of ways.

In chapter 2, unlike past research that treats consumer effort as a singular and subjective measure (see Bechwati and Xia 2003; Hong, Thong, and Tam 2004; Wang and Benbasat 2009), we distinguished two sources of consumer effort related respectively to the outcome (information-based effort) and the process of information gathering (interaction-based effort). We showed that consumer effort can be reduced in two ways. First, consumer effort can be reduced by providing more dense and tailored content based on user needs and, second, by allowing users to decide on the way the informational content is accessed (capturing the way in which users interact with the website). Moreover, we pinpoint the role of content learning in information communication and its impact on users' further behavioral outcomes. The amount of information that consumers absorb from their visit to a content-based website can signify their goal effectiveness and influence their attitude towards the website. Although content learning is proposed to be the link between obtained information and further behavior (Vandenbosch and Higgins 1996), past studies in online decision making primarily focused on procedural knowledge and skill acquisition (Murray and Häubl 2002). We proposed that content learning plays a greater role in content-based websites, and relates to the declarative level of knowledge formation that consumers succeed. The amount of information that users learn in a content-based website can signify their individual performance which, in turn, can influence their attitude towards the website. In addition, we demonstrated how content learning is influenced by different specifications of information and interaction-based user effort requirements. In this line of thought, we argued that increasing consumer effort is not necessarily a bad approach, but it rather depends on the source and nature of the additional required effort. Finally, we expand the literature regarding content-based websites and we provide evidence of the importance of consumer effort and learning in improving their effectiveness.

In chapter 3, we extend the common strategy of online firms when attempting to promote a better understanding of their products. Traditionally, online firms focus on providing more and richer product information to consumers. However, we proposed that differences in the composition of the product choice sets that are offered to consumers may also affect consumer product knowledge. Therefore, even if consumer effort is increased due to the complexity of the choice set, that may lead to favorable results. More specifically, we showed that increased choice set complexity (measured by the interattribute correlation and attribute range) increases the ability of consumers to remember the components of the encountered choice set. However, this effect may be overshadowed by the decrease in the subjective knowledge assessment that complex choice sets accentuate. Therefore, we provided additional support on the current assumption that the two components of consumer knowledge should be disentangled (Moorman et al. 2004). In addition, we validated the managerial meaning of the effect of choice set complexity on consumer product knowledge by providing evidence for its influence on consumer product conversion and willingness to pay for the chosen alternative. Finally, we provide a more generalizable framework by finding support of our expected relationships in two distinct product categories (a rather utilitarian and costly compared to a more hedonic and less expensive) and across distinct methods of data collection (clickstream data analysis versus experimental study).

In chapter 4, we investigated the different effects of time related consumer effort across different website sections within a given visit in a product recommendation website. Whereas extant literature on decision time has showed contradictory findings regarding its effect on conversion probability, we present an alternative approach that can explain this conflict. In this chapter, we argue that decision time is not a one-dimensional construct but can rather be disentangled into further dimensions that can explain these oppositional indications. We suggest a decomposition of total decision time into product and choice set level inspection time, and show that the opposing findings in the literature regarding the effects of time on can be explained in such a way. We find that attractiveness of a choice set increase the expected utility of the choice and therefore increase product level inspection time. In such a case more time related effort of consumers can be beneficial for the online firm. In parallel, increased complexity of a choice set may lead to higher choice set level inspection time, which in turn decreases the chances of conversion. Thus, it is very important to understand how consumers on a website allocate their time during a visit and what drives this allocation. An improved understanding of how the composition of an offered choice set influences the allocation of time and how different time allocation decisions may lead to different behavioral outcomes affects the success and performance of the website and is critical for online firms. Therefore, the important question for websites is not how much time consumers spend on site but rather how consumers distribute this time to different pages and tasks. Although the concept of time spent has a long tradition in marketing and economic literature (Jacoby, Szybillo and Berning 1976; Otter, Allenby and Van Zandt 2008), this is the first study that attempts such a decomposition of actual time spent on a website in order to predict website conversion. We also provide evidence that the complexity of a choice set increases the time related consumer effort. This suggests that the complexity of the choice hardens the task of the consumer and therefore this expected drawback is filtered through the increased choice set level inspection time which negatively influences the conversion likelihood. By using real life clickstream data to support our propositions, we can give a more convincing support for the consistency of our findings.

5.3 Managerial Implications

Apart from generating new substantive insights, our findings have a number of implications for business practitioners that we discuss next in the form of managerial implications. An improved understanding of how consumer effort in a website can affect the success and performance of the website itself is critical for online firms (Liu, Sarkar, and Sriskandarajah 2010). Our findings on the differential effects of consumer effort on various behavioral outputs underline the conclusion that the emerging issue in question is not whether to reduce consumer effort or not, but rather how to reduce it. Therefore a better understanding of user effort may help online firms that need to evaluate the benefits of making investments in their websites to reduce user effort in order to justify the cost associated with such processes.

In chapter 2, we provide a better understanding on when and how different approaches of effort reduction based on information personalization can have optimal results for information intensive websites. We show that user effort reduction is not a one dimensional venture. By distinguishing between two discrete dimensions of user effort, we can explain some of the debatable findings regarding the role of effort. 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 full service, though it may seem attractive to them, does not necessarily lead to more beneficial user behavioral responses. It is therefore important for online information providers to be aware of the options of information communication to increase user learning. In addition, we highlight the role of content learning as a determinate of the effectiveness of the various approaches of user effort reduction. Online firms can benefit from these results, since they may improve the returns on the vast investment in these technologies, by making the process of content learning on their websites easier to their users. 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.

In chapter 3, we show that also in transactional websites, consumer effort can have opposing effects on consumers. We show that an additional source of consumer effort is based on the composition of the recommended choice sets. From a managerial standpoint, in many domains where complex products are sold, companies are responsible for guaranteeing their consumers' product understanding. The joint effort of consumer learning and company learning can significantly improve consumer purchase decisions, which in turn drives consumers' repeat visits. We show that product knowledge can be influenced by manipulating the composition of the offered set of recommendations. Companies can benefit by gaining deeper insights on the mechanism behind consumer knowledge. It is very important for companies to understand how to improve the product understanding of their customers without additional costs and investments (i.e. costs to implement and to train the users). However, online firms should be cautious with involving their customers in increasingly easy choices, since this approach can be overtaken by the decreased objective knowledge. Conversely, by increasing the choice set complexity, consumers feeling of knowing declines. In complex choice sets, consumers might be able to absorb better the information, but they feel less confident about it. As a result, companies should investigate the optimal point of this trade-off between objective and subjective knowledge. In addition, we provide evidence about the managerial importance of consumer product knowledge. Both objective and subjective knowledge positively influence the decision to buy.

Based on our finding in chapter 4, online firms can benefit to improve the composition of the offered product choice sets by taking into consideration the allocation of time spent by consumers on a given session and by balancing between consumers' time at the choice and at the product level. The same choice set may vary in terms of attractiveness and complexity across customers. Decision time and more specifically, its allocation across product and choice set level can offer a good process level validation of the subjective attractiveness and complexity of a choice set. Companies can benefit by tracking the time allocation of their online visitors and outline their preferences and distinctive characteristics. By disentangling inspection time, we improve the current web metric approach of total time on a website. Business web metrics measure "time on site" or "duration of a visit" as an indication of effective web traffic". We show that trying to increase the time spent on a given website does not have the same effect in all the web pages. Website owners should attempt to increase duration in specific parts of the website and shift the time allocation in a given session towards product inspection parts. In addition, an additional interesting finding is that there is a trade-off between attractiveness and complexity in a choice set. Whereas normative theory would suggest that companies offer the best options to the consumers so that the probability of purchase incidence increases, we show that offering multiple close alternatives (even though highly attractive) in a choice set increase the difficulty of consumers' choice. As a result, choice set inspection time increases and therefore the online conversion chances may drop. This is very important especially in the case of product intermediaries. These websites do not have control over the product attractiveness of what they can offer, but rather they can influence the composition and choice difficulty of the offered choice sets. Therefore, the inclusion of more distant alternatives can increase the conversion probability in their website.

5.4 Avenues for Future Research

In this final part of the dissertation, we discuss some limitations across the three empirical studies of this dissertation and propose some avenues for future research regarding the topic of consumer effort.

Whereas we show that in content-based websites, higher consumer effort can have beneficial effects for both the firm and the user, a remaining issue in question is how firms can convince users to select these “high effort” interfaces. We show that one of the main reasons for the effectiveness of some sources of high consumer effort is the information absorption. However, consumers should be convinced about the merits of having to put more effort in a task. Therefore, it would be interesting to investigate what makes users choose among different information formats that differ in terms of required effort. 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.

We recognize the limitations of using recall for operationalizing content learning or product knowledge. Recall tests have been extensively used in past studies as a measure for learning especially when there is a goal-directed behavior (Hong, Thong, and Tam 2004; Kanwar, Grund, and Olson 1990). However, recall is more related to short-term memory effect whereas learning is a more long term construct (Park, Mothersbaugh, and Feick 1994). One way to overcome this problem is to repeat a recall test in a future encounter. However, in order to apply such an approach, an incentives-based study should be implemented so that it can highly resemble actual behavior. 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. 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 to focus on subjective knowledge which is more related to the self-efficacy of the users and might influence their behavioral outcomes especially in content-based websites (Bandura 1997; Park, Mothersbaugh, and Feick 1994).

In addition, we draw on the idea of information overload to suggest that providing more extensive information (content or product related) 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 user effort that can maximize learning and further improve behavioral outcomes.

Respectively, cognitive load might also incur after too much time spent on inspecting (see chapter 4) or when a choice set is too complex (see chapter 3). For example, when a choice set becomes extremely complex, consumers might start using compensatory heuristics in order to facilitate their choice process. As a result, objective knowledge would decrease and the confidence of their knowledge is expected to improve. Although an inverted-U relationship was not found in these studies, it may be attributed to the limited range and variation of the informational stimuli. Therefore, we expect that within some typical time thresholds, cognitive load is not activated.

Also, the valence of the accessed information (especially if product related) may alter the role of additional effort in a given task. A non-linear effect may be met also if there is almost no variation in the product related information. In such a case, consumers may find no substantial differences between options and as a result they stop putting effort in a task. In terms of choice complexity, we use the interactions between interattribute correlation and attribute range within a choice set. However, it would be insightful to introduce additional components such as the number of the alternatives or attributes presented to the consumers, or the relative attractiveness of the choice set. Finally, it would be interesting to examine the effects of choice set complexity as well as consumer product knowledge on different behavioral outcomes of the consumers. It is expected that consumer knowledge would increase the decision quality and satisfaction of the consumers. However, the influence of choice set complexity on these outcomes would highly depend on the role of the two knowledge components and what is the weight that implicitly consumers assign to each of them. Finally, information search patterns may differ based on the nature of the product searched (Huang, Lurie, and Mitra 2009). In our empirical application we used rather complex and durable contexts. It would be interesting to see whether these findings still apply in a more hedonic and impulsive buying situation.

Summary in English

The overarching goal of this dissertation is to study the role of consumer effort within the context of online decision-making. With the rise of online channels, consumers have the opportunity to access a great amount of sources before making a decision due to the reduced switching barriers. Online firms have introduced decision aids to assist consumers cope with information overload and reduce their effort. In such a way, firms improve their service efficiency by enhancing consumers' decision quality and reducing their effort. Consumers are driven by the twofold goal of jointly maximizing the accuracy of their decisions and minimizing their required effort in order to achieve that level of decision quality. Consumers face various types of cost, such as for example the physical, cognitive, or financial cost. Effort is perceived as a form of cost for consumers and therefore they wish to minimize it (principle of least effort). However, by minimizing the effort in a task, users jeopardize the quality of their decisions. On the other hand, consumers consider effort as an investment in that it increases the likelihood of making a good decision. Based on 3 studies, we attempt to show that consumer effort may not be necessarily malevolent and that some sources and measures of greater consumer effort can even lead to beneficial outcomes. A better understanding of the role of consumer effort may help firms that need to evaluate their investments in reducing consumer effort and justify the cost associated with implementing such a strategy.

In the first study, we suggest that user effort reduction in a content-based website (i.e. health portal) is not always beneficial. Consumer effort can be decreased either by reducing the size of the content or by decreasing the involvement of users in the process. Respectively, the dimensions of information and interaction-based user effort are introduced. Information-based user effort reduction leads to beneficial behavioral outcomes (website evaluation and revisit intention). However, interaction-based user effort reduction has the opposite effect. We show that the opposing effects of effort reduction can be attributed to the mediating role of content learning. In the second study, we use the complexity of the composition of the recommended choice set as a source of consumer effort. Although, in order to promote consumer product knowledge, firms often focus on providing more and richer product information to consumers, we suggest that differences in the composition of the product choice sets can also affect consumer knowledge. We examine the role of product knowledge in a transactional setting where product information is communicated to consumers in the

form of product recommendations. We propose that greater choice set complexity (which increases consumer effort) increases objective consumer knowledge due to greater required cognitive elaboration throughout decision making process. At the same time, greater complexity decreases consumer choice confidence and lowers subjective product knowledge. Finally, we validate that the effect of choice set complexity on product knowledge is managerially meaningful in that it influences website conversion and willingness to pay for the chosen alternative. In the third study, we examine the role of time as a measure of consumer effort in the context of online product recommendations. Marketing research results on whether firms should increase or decrease consumer decision time to boost website conversion rates are mixed. While some studies suggested the positive impact of inspection time since it lowers consumer product uncertainty, others have emphasized its negative effects due to increased consumer effort and the opportunity costs that come with it. We disentangled consumer inspection time into two components that are hypothesized to have opposing effects on website conversion: choice set and product-level inspection time. We predict that at the choice set level, inspection time is determined by the complexity of the choice set and decreases website conversion. However, at the product level, greater inspection time effort reflects a greater expected utility, and increases conversion. By analyzing clickstream data from financial product recommendations, we show that consumer time effort can be beneficial at a product level and accordingly suggest improvements on the composition of the recommended choice sets.

Nederlandse Samenvatting (Summary in Dutch)

Het doel van dit proefschrift is het bestuderen van de rol van inspanningen door consumenten binnen de context van online besluitvorming. Met de opkomst van online kanalen hebben consumenten toegang gekregen tot een groot aantal bronnen die ze kunnen raadplegen alvorens een besluit te nemen. Dit vermindert de belemmeringen om over te stappen. Online bedrijven hebben beslissingshulpmiddelen geïntroduceerd om consumenten te assisteren bij het omgaan met een overvloed aan informatie en het verminderen van hun inspanningen. Op deze manier verbeteren bedrijven hun de efficiëntie van hun dienstverlening door de kwaliteit van de beslissingen dieconsumenten nemen te verbeteren en tegelijkertijd de van consumenten vereiste inspanningen te verminderen. Bij het nemen van beslissingen worden consumenten geconfronteerd met verschillende typen kosten, zoals fysieke, cognitieve, en financiële kosten. Door cognitieve inspanningen te minimaliserenzetten consumenten echter de kwaliteit van hun beslissingen onder druk. Op basis van drie studies onderzoeken we daarom of inspanningen bij het nemen van beslissingen niet noodzakelijk een slechte zaak zijn voor consumenten. We tonen aan dat sommige bronnen en vormen van grotere inspanningen door consumenten zelfs kunnen leiden tot positieve uitkomsten. Een beter begrip van de rol van inspanningen door consumenten kan bedrijven daarom helpen bij het evalueren van hun investeringen in het verminderen van inspanningen door consumenten en het verantwoorden van de kosten die gepaard gaan met het implementeren van een dergelijke strategie.

In de eerste studie stellen wij dat de rol van inspanningen door consumenten op een 'content-based' website (in dit geval een portal over gezondheid) soms positief en soms negatief is. De dimensies van informatie- en interactie-gebaseerde inspanningen door consumenten geïntroduceerd. Inspanningen van consumenten kunnen verminderd worden door of de omvang van het (inhoudelijk) informatie materiaal of de interactiemet gebruikers bij het proces te verminderen. Informatie-gebaseerde inspanningen leiden tot lager website evaluatie en intentie voor terugkerend bezoek. Interactie-gebaseerde inspanningen hebben het tegengestelde effect en leiden tot hogere evaluaties. Wij tonen aan dat de tegengestelde effecten van inspanningsverminderingen toegeschreven kunnen worden aan de mediërende rol van het beter leren wat er op de website wordt verteld. In de tweede studie onderzoeken we de rol van productkennis in een online verkoopomgeving waar productinformatie wordt gecommuniceerd aan consumenten in de vorm van productaanbevelingen. Bedrijven concentreren zich vaak op het aanbieden van meer en gedetailleerdere productinformatie om de productkennis van consumenten te vergroten. Wij stellen echter dat ook de samenstelling van de productkeuzesets ook de kennis van de consumenten kan beïnvloeden. Wij variëren de complexiteit van de samenstelling van de keuzeset en daardoor ook de vereiste cognitieve inspanningen door consumenten. Wij voorspellen dat grotere complexiteit van de keuzeset de objectieve kennis van consumenten vergroot vanwege de toegenomen cognitieve verwerking die nodig is gedurende het besluitvormingsproces. Tegelijkertijd verlaagt deze grotere complexiteit echter het vertrouwen van consumenten in hun gemaakte keuze en hun eigen subjectieve productkennis. Ook gaan we na of het effect van de complexiteit van de keuzeset op productkennis van invloed is op websiteconversie en de bereidheid van consumenten om meer te betalen voor het gekozen alternatief. In de derde studie ten slotte onderzoeken we de rol van beslistijd bij keuzes van consumenten in de context van productaanbevelingen. Eerdere onderzoeksresultaten over de vraag of bedrijven de beslistijd van consumenten moeten verhogen of verlagen om websiteconversie te vergroten zijn niet altijd eenduidig geweeste. Terwijl sommige studies stellen dat er een positieve invloed van inspectietijd is omdat het de productonzekerheid van consumenten verlaagt, benadrukken andere studies de negatieve effecten van grotere inspanningen door consumenten en de opportuniteitskosten die daar mee gemoeid zijn. Wij ontrafelen consumenten inspectietijd in twee componenten waarvan wij verwachten dat zij tegengestelde effecten hebben op websiteconversie: inspectietijd op het niveau van de keuzeset en inspectietijd op het productniveau. Wij voorspellen dat inspectietijd op het niveau van de keuzeset wordt gedreven door de complexiteit van de keuzeset en daarom websiteconversie doet afnemen. Echter, op het productniveau weerspiegelt een langere inspectietijd een hogere verwacht nut voor de consument en verhoogt daarom de conversie. Door het analyseren van 'clickstream' gegevens van financiële productaanbevelingen, kunnen we laten zien dat tijdinspanningen door consumenten inderdaad gunstig kunnen zijn op het productniveau. In lijn met deze bevindingen stellen wij tot slot aanbevelingen voor met betrekking tot de samenstelling van de aan consumenten aangeboden keuzesets.

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NO PAIN NO GAIN
THE BENEFICIAL ROLE OF CONSUMER EFFORT IN DECISION-MAKING

The overarching goal of this dissertation is to study the role of consumer effort within the context of online decision making. We show that consumer effort may not be necessarily malevolent and that some sources and measures of greater consumer effort can lead to beneficial outcomes. A better understanding of the role of consumer effort may help firms evaluate their investments in reducing consumer effort and justify the cost associated with implementing such strategies. First, we suggest that user effort reduction can be beneficial when it concerns the amount of information but not when it regards consumer involvement in the process of getting the information. These opposing effects can be attributed to the mediating role of content learning. Second, we use the complexity of the composition of the recommended choice set as a source of consumer effort and we propose that greater complexity increases objective consumer knowledge due to greater cognitive elaboration but decreases choice confidence and subjective product knowledge. Third, we examine the role of time as a measure of consumer effort in the context of online product recommendations. We distinguish between consumer inspection time-based effort at the choice set and at the product level and suggest that whereas at the choice set level, inspection time decreases website conversion, at the product level, greater inspection time has the opposite effect. Accordingly we suggest improvements on the composition of the recommended choice sets in a way that the allocation of consumers' time spent is effectively balanced.

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