UNIVERSITY OF TWENTE – BMS FACULTY

ONLINE SHOPPING ABANDONMENT RATE A NEW PERSPECTIVE

THE ROLE OF CHOICE CONFLICTS AS A FACTOR OF ONLINE SHOPPING ABANDONMENT

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Abstract

The high rates of online shopping abandonment are a major problem in a trillion dollar industry. In this research we focused on the extent to which choice conflicts influence online shopping cart abandonment. We began by investigating exploratorily the nature, frequency, and sources of choice conflicts as they manifest themselves in the online environment. Next, we studied experimentally the effects of choice conflicts on the shopping cart abandonment using a custom developed webshop to replicate a real online shopping session. For this purpose, we used a 2x3 factorial experimental setup and we analyzed data from 164 participants. We found that choice conflicts were not a direct cause of online shopping abandonment. Instead, results indicate that with each experienced choice conflict, the chance of a perceived higher decision difficulty increased 17 times. Subsequently, a perceived higher level of decision difficulty increased the chance of abandoning the shopping cart by 22%. Additionally, we found that the effort to search information and product attribute alignment also influenced the perceived decision difficulty; at the same time, maximizing behavior was identified as the main source of choice conflicts. The resulting research model illustrates the conjoint effect of choice conflicts and perceived decision difficulty on increasing the chance of online shopping abandonment. We found that displaying products with nonaligned attributes decreased the perceived decision difficulty and reduced the chance of shopping abandonment. Further research is needed to develop methods to lower the chance of experiencing choice conflicts and high decision difficulties.

Keywords: decision making, choice conflicts, online shopping, shopping cart abandonment, ecommerce, webshop, maximizing tendency, maximization behavior, attribute alignment, information search effort, perceived decision difficulty

> "*[The internet is] the ultimate customer-empowering environment. He or she who clicks the mouse gets to decide everything. It is so easy to go elsewhere; all the competitors in the world are but a mouse click away*" (Nielsen, 1999, p. 9).

1. Introduction

The online environment is characterized by the abundance of choices and information. Searching this vast, information-rich space is easy and offers the prospect of finding (almost) anything online (Scheibehenne, Greifeneder, & Todd, 2010). In this promising environment ecommerce developed rapidly into a market in which over 1 billion shoppers spent more than 1.5 trillion dollars in 2014 and shows no signs of slowing down in the future (eMarketer, 2013, 2015). While the amount of information and options available on the internet increased the freedom of possibilities, the process of making a decision online became fuzzy and complex. Simply assuming that all possibilities are "just a click away" lured online users into the belief that a best option is somewhere out there and that all they need to do is to find it (Schultz & Block, 2015).

When buying something online shoppers use on average around twelve sources of information (e.g. webshops, review websites, social networks, and the like) before making a decision (Thomas, Dean, Smith, & Thatcher, 2014). In this process a shopper scans, evaluates and compares the offering of 4 to 5 different webshops and spends up to 15.8 hours researching online (Google and Ipsos MediaCT, 2014). Consequently, it turns out that making a choice when shopping online is nowadays not as easy as it was advocated and predicted 15 years ago (Alba et al., 1997; Nielsen, 1999). Indeed, looking at the conversion rates in ecommerce, it seems that consumers more often choose to abandon the shopping cart instead of purchasing (for instance the 1.1% average conversion rate in US electronics e-shopping, according to Najafi index, 2014).

From both business and scientific perspectives, researchers and practitioners have investigated the problem of online shopping abandonment, trying to understand and address the causes of such low conversion rates (Egeln & Joseph, 2012; Google, 2014; Henneberry, 2012; Kukar-Kinney & Close, 2010; Moshrefjavadi, Dolatabadi, Nourbakhsh, Poursaeedi, & Asadollahi, 2012; Statista, 2015; Xu & Huang, 2015). They concurred mostly on the following factors: lack of transparency with regard to transaction and delivery costs, difficult website navigation, complicate ordering process, size of the consideration set, size of the offered alternatives, and trust in the online merchant, to be among the main determinants for cart abandonment.

Based on those findings, specialists have created online guidelines, handbooks, blog posts, infographics, and conferences for helping the business community understand how to optimize their webshops in order to decrease the rate of shopping cart abandon (Henneberry, 2012; Macdonald, 2013). With such information available, it is expected that at least the big players in the online shopping industry (such as Amazon.com, Coolblue.com, or Bol.com, etc.) would have adopted measures for optimizing their webshops. Nonetheless, with an averaged global shopping cart abandonment rate around 68% reported by Baymard Institute (2014) in an extensive review, it seems that the problem of shopping cart abandonment in the online commerce remains.

Take, for example, bol.com, a familiar e-commerce website for the Dutch online market and a leader in Benelux countries (Ecommerce-News, 2015). There are no hidden costs in the shopping process, they offer free delivery for orders over 20 euros, the offering covers a broad range of categories and tastes and price levels, they show customer reviews for products, and maintain a transparent, easy and short ordering process. Also they are well known on their core market. Yet, the bol.com average conversion rate in 2014 was around 5% (Ropers, 2014). To sum up, the shopping cart abandonment problem in the online environment is not fully understood.

A WorldPay report gave indication of a new path in studying the abandonment phenomenon. Accordingly, 26% of the shoppers reported “decided against buying” as a reason for online shopping abandonment (WorldPay 2014 cited in Statista (2015)). However, there is not enough information about the operationalization of the concept, thus it is not very clear what exactly made consumers to “decide against buying”.

The present research brings in the spotlight this “decision against buying”, focusing on the consumer decision making process and the reasons for abandoning the purchase. We use the findings of Tversky and Shafir (1992) as the starting point because they proved in several experiments that consumers confronted with a choice conflict usually decide to defer choice and not buy anything. Therefore, the main research question is “**To what extent do choice conflicts influence the shopping cart abandonment rate in online shopping?**”.

Because there is limited knowledge of choice conflicts in the online environment, first it is important to understand how choice conflicts manifest in the online shopping situations, and then to find out how likely the choice conflicts are to occur in the online environment. In this respect, we formulate three preliminary exploratory research questions. The first exploratory research question is “what are the sources of choice conflict in the online shopping environment?”., the second question investigates “how often choice conflicts occur when shopping online?” and the third exploratory question regards “what consumers do to resolve a choice conflict when shopping online?”.

We argue that observing consumers while shopping online will help answering these preliminary questions, which will extend the knowledge about choice conflicts in the online shopping situations and will provide the arguments for researching the main question of the study. In this respect the present study follows the empirical research method formulated by Adriaan de Groot, because first we will observe and then we will approach the inductive phase of the empirical cycle (Dooley, 2001; Groot & Spiekerman, 1969).

This research contributes to the extensive body of research regarding consumer behavior in online shopping situations and shopping cart abandonment (Close, Kukar-Kinney, & Benusa, 2012; Fernandes, 2012; Kooti et al., 2015; Xu & Huang, 2015).

The findings will provide new theoretical meaning and understanding of the online shopping decision making process as a whole, and of other factors that influence purchase abandonment. Managerial and marketing implications are also expected, as this research is likely to extend the knowledge of factors that influence shopping cart abandonment rates. Finally we hope that our findings will set the stage for designing new decision support systems for leveraging decision paralysis in online shopping situations, making it easier for consumers and businesses to achieve their goals.

2. Literature review

The research project is built on the foundations of the choice conflict concept which states that consumers confronted with different, but equally attractive options have a hard time in making a choice for one of the alternatives.

Tversky and Shafir (1992) showed that when the choice conflict situation is difficult to solve, consumers will delay the decision and abandon the purchase. Their experiments were replicated in a series of studies which identified similar decision avoidance behavior when confronted with choice conflicts (see Chernev, Böckenholt, & Goodman, 2015 for a review). The following section investigates the literature for defining the main concepts used in this study.

2.1. Choice conflict

Conflict in decision making contexts is defined by the existence of two or more options that are equally attractive but in different aspects (Tversky & Shafir, 1992).

When confronted with such options, a decision actor constrained to choose one alternative will experience difficulty in choosing (Dhar, 1997). In this case the conflict is high and, in order to resolve it, one must sacrifice (trade) some desired attributes of one alternative against different preferred attributes of another alternative. However, because people are not always able to make these tradeoffs, Tversky and Shafir (1992) stated that in such cases consumers will opt for choice deferral and will abandon the decision process. Conversely, if one alternative is better in all desired aspects, then it dominates the others and thus the conflict is low. In this case, one can solve it easily by simply choosing the better (dominant) option (Shafir, Simonson, & Tversky, 1993).

To illustrate this, imagine the following scenario, adapted from Tversky and Shafir (1992) in which one has to choose between a trip to Rome, all expenses paid, or a trip to Paris, all expenses paid. Both options are equally attractive, but not identical. One can experience great difficulty in choosing between the two alternatives because one has to make trade-offs. In this case the choice conflict is high. Now, consider the following: choose between one trip to Rome, one trip to Paris, all expenses paid, and add one trip to Rome, all expenses paid but coffee is not included; you have to buy your own coffee. Now, simply adding the inferior option without coffee made the option Rome with coffee more attractive. In this scenario choice is easier because Rome with coffee dominates both alternatives (see also Ariely & Jones, 2008 for more examples).

Choice conflict is influenced by attribute alignment, the number of available options and the information search effort (Jing, Zixi, & Dhar, 2013; Tversky & Shafir, 1992).

It was observed that people experience high conflict when there are more available options with non-aligned attributes. In this situation consumers tend to expend more search effort in an attempt to resolve the conflict by reaching to a dominant alternative (Dhar, 1997; Tversky & Shafir, 1992).

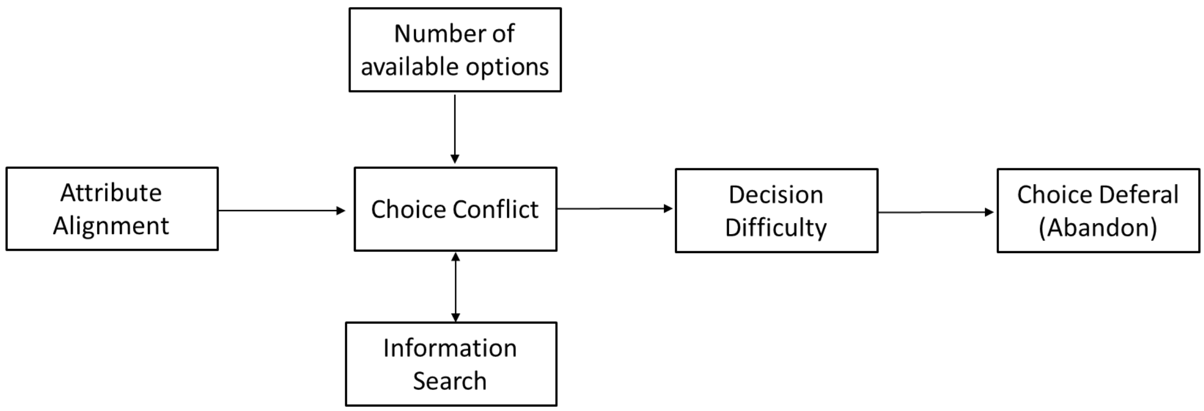

Figure 1 - Choice Conflict Model, adapted from Tversky & Shafir (1992)

However, searching for more options means more comparisons, which heightens the difficulty to choose, hence increasing the chance to abandon the decision (Iyengar & Lepper, 2000; Jing et al., 2013). The choice conflict model is summarized in figure 1.

2.2. Decision difficulty

Within the decision context difficulty can be expressed as an unpleasant state that requires effort to be dealt with. In general decision actors experience various levels of difficulty during the decision making process, originating from two primary sources: cognitive and emotional difficulty (Luce, Bettman, & Payne, 2001).

Cognitive difficulty is related mostly to information processing aspects, while emotional difficulty is rooted on the judgments about the consequences of the decisions. For example, a decision is cognitively difficult when the task is complex, when the available information is scarce or incomplete, or when there is conflict between the attributes of different considered options.

Emotional difficulty involves a decision whose implications could threaten several significant goals of the decision maker. Luce et al. (2001) argue that trading some desired attribute levels of one alternative in order to gain something on another is among the main sources of emotional decision difficulty.

The two basic sources for decision difficulty are not influencing the decision process separately. Instead, Luce et al. (2001) show that emotional and cognitive difficulty interact with each other, information processing difficulties exacerbating the emotional trade-off difficulty.

Decision difficulty is strongly linked to the choice conflict generated by various cognitive and (or) emotional factors. Although decision makers have strategies for coping with decision difficulty in general, trade-off difficulty is considered to counterbalance the coping strategies by heightening the loss-aversion function (Kahneman & Tversky, 1979). As a result, it is expected that more difficult trade-offs will amplify the sentiment of losing which induces a preference for maintaining the status-quo (i.e. decision to defer choice).

2.3. Attribute alignment

Attribute alignment refers to the structural differences of the attributes describing an object (Gentner & Markman, 1994). According to the Structural Alignment Theory (Gentner & Markman, 1994; Markman & Medin, 1995) attribute alignment is central to the process by which consumers make comparisons, evaluate and distinguish between alternatives. By extending the theoretical framework to decision making, Markman and Medin (1995) separate attributes along one bi-polar dimension of alignment: aligned and nonaligned.

Aligned attributes are defined as the attributes found on all considered alternatives, but varying at different levels across them. For instance, phone camera resolution is an aligned attribute if one has a 5 megapixels phone camera, while another has a 3 megapixels one. It is evident that the phone with a 5 megapixels camera is the dominant option and will likely be selected by the decision maker. These attributes offer information for comparing the similarities between alternatives, providing support for distinguishing the dominant alternative (Gati & Tversky, 1982). As such, making a choice between alternatives with aligned attributes involves lower conflict because the alternatives are comparable and it is easier to construct a dominant alternative (Markman & Medin, 1995; Tversky & Shafir, 1992).

Nonaligned attributes are not shared by all alternatives in the considered set, or do not present desired levels. For example, one phone has a 3 megapixel camera and no memory storage, and another phone has no camera at all and 1024 MB of storage space. Deciding for the camera attribute involves sacrificing the memory storage, whereas desiring more storage space means trading the phone camera. Decision making in these situations involves trade-offs because the alternatives are not comparable, inducing higher levels of effort in discriminating between them (Gentner & Markman, 1994; Markman & Medin, 1995; Zhang & Fitzsimons, 1999). The structural alignment model predicts that consumers will expend effort to construct a comparable set of alternatives by trading some attributes for others in order to establish alignability across alternatives (Markman & Medin, 1995). According to Tversky and Shafir (1992) this increases the choice conflict because of an equivocal situation: consumers cannot discriminate the dominant alternative. To resolve the conflict consumers engage in information search (Urbany, Dickson, & Wilkie, 1989). Because searching for information takes more time and effort, the decision process becomes increasingly difficult. In this situation people are more inclined to defer choice and abandon the decision (Shafir et al., 1993).

2.4. Information Search

In general, information search is a process aiming to reduce the uncertainty (Wilson, 1999). In the context of this study information search is seen as the activity performed in order to resolve choice conflicts (Urbany et al., 1989). Searching for information requires the allocation of cognitive resources such as “attention, perception, and effort directed toward obtaining […] information related to the specific purchase” (Beatty & Smith, 1987, p. 85). The cost of expending such resources is called information search effort. The Theory of Bounded Rationality (Simon, 1972) predicts that consumers will optimize the information search by satisficing, because the capacity of their resources is limited. In this respect, satisficing is the strategy for selecting the good-enough option.

Tversky and Shafir (1992) state that the tendency to engage in information search depends on the availability of other alternatives. They argue that consumers will spend effort to evaluate other options when experiencing choice conflicts, provided that new alternatives are available. This contradicts the satisficing principle from the bounded rationality theory, which assumes that information search effort is independent from the number of available alternatives (Simon, 1972).

Schwartz and colleagues have a different view on the relationship between information search and the number of alternatives available which concurs with Tversky and Shafir's finding. They show that search for information is in fact influenced by the number of available options, but the relationship is moderated by the maximizing tendency (Dar-Nimrod et al., 2009; Schwartz, 2004). The reason is that more choice increases the likelihood of finding the best available option

(Iyengar, Wells, & Schwartz, 2006). In this sense, maximizing is the tendency to search for the best available option. Individuals with higher tendency for maximizing are inclined to engage in extensive search for information. In doing so they expend more effort, experience more difficulty, higher levels of choice conflicts and are prone to abandon the decision process.

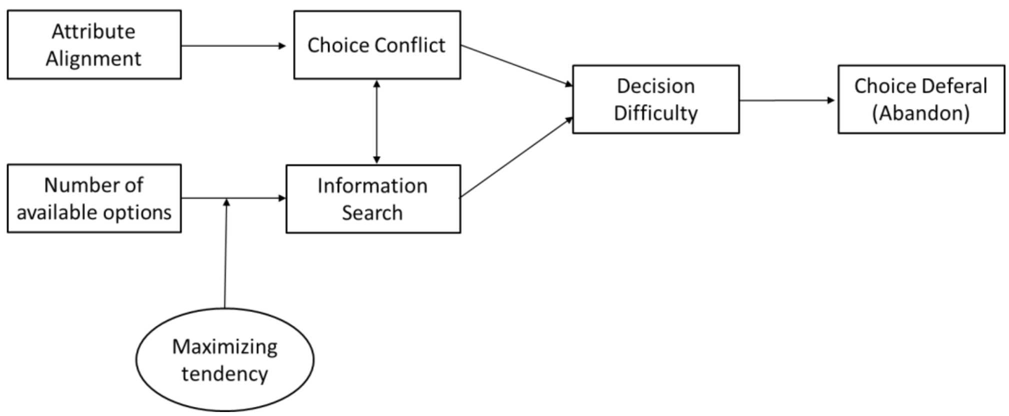

Figure 2 - Choice Conflict Model including Maximizing tendency as a moderator for the intensity of information search effort. Adapted from Tversy & Shafir (1992) and Dar-Nimrod, Rawn, Lehman, and Schwartz (2009)

Because in the online environment the available choices are virtually unlimited we expect that consumers will engage into extensive information search while shopping online. In this way we think that including maximizing tendency in the initial model of choice conflict will make the model more appropriate for studying the choice conflict in the online environment.

2.5. Maximizing

Maximizing is defined as the tendency to find and select the best option from a given set of alternatives (Schwartz et al., 2002). This requires intensive allocation of resources for evaluating exhaustively a set of available alternatives (Rim, Turner, Betz, & Nygren, 2011).

In the bounded rationality framework, maximizing is considered improbable because decision actors have only "incomplete information about alternatives" (Simon, 1972, p. 163) and the cost of reducing the uncertainty increases exponentially. Therefore the theory implies that instead of engaging in a maximizing behavior, people follow a satisficing strategy for achieving the good-enough option from a set of alternatives. From the bounded rationality point of view, satisficing behavior is a universally manifested tendency; any "rational" person will seek for the good-enough option.

Contrary to the bounded rationality theories, Schwartz et al. (2002) see the concept of maximizing/satisficing as an individual trait. In their opinion maximizing and satisficing are two extremes between which people vary on a bipolar continuum. Individuals closer to the maximizing side have the tendency to expend more effort for finding the best option, while those closer to the satisficing end settle with a good enough option and do not involve themselves into extensive search. Schwartz (2004) suggests that maximizers are more likely to experience regret and depression, while satisficers (e.g. people with lower scores on maximizing dimension) are more likely to experience well-being . However, other studies reported disagreement for the view of maximization as opposed to satisficing, advocating against the uni-dimensionality of construct (Highhouse, Diab, & Gillespie, 2008; Rim et al., 2011; Turner, Rim, Betz, & Nygren, 2012). They observed that if measured separately, the inclination to satisfice is not the reverse of the tendency to maximize, meaning that individuals can be both maximizers and satisficers at the same time, thus contradicting the bipolar nature of the construct, assumed by Schwartz and colleagues.

The maximizing tendency can be measured with the Maximization Tendency Scale (MTS, 9 items, α=.80) developed by Highhouse et al. (2008) as an improved version of the original Schwartz et al. (2002) maximization scale (MS), or with the Maximization Inventory (MI, 34 items, α=.72 to .89) developed by Turner et al. (2012). Maximization Inventory proposes a multidimensional measurement instrument consisting of three subscales: decision difficulty (12 items, α=.89), alternative search (12 items, α=.82), and satisficing tendency as a separate construct (10 items, α=.72). For the Maximization Inventory only the first two subscales are related to the maximizing tendency, while the latter measures the satisficing tendency.

2.6. Preliminary research model

Based on the review of literature regarding the role choice conflict plays in the decision making process we have sufficient arguments to consider choice conflict as a major source for decision difficulty. In this respect, choice conflicts are generated especially by the loss aversion induced by trading-off equally attractive alternatives with different attributes.

Decision actors try acquiring more information as a strategy for resolving trade-off generated conflicts. However, the effort of processing more information adds up to the initial conflict and can increase the decisional difficulty which leads to choice deferral and decision abandonment.

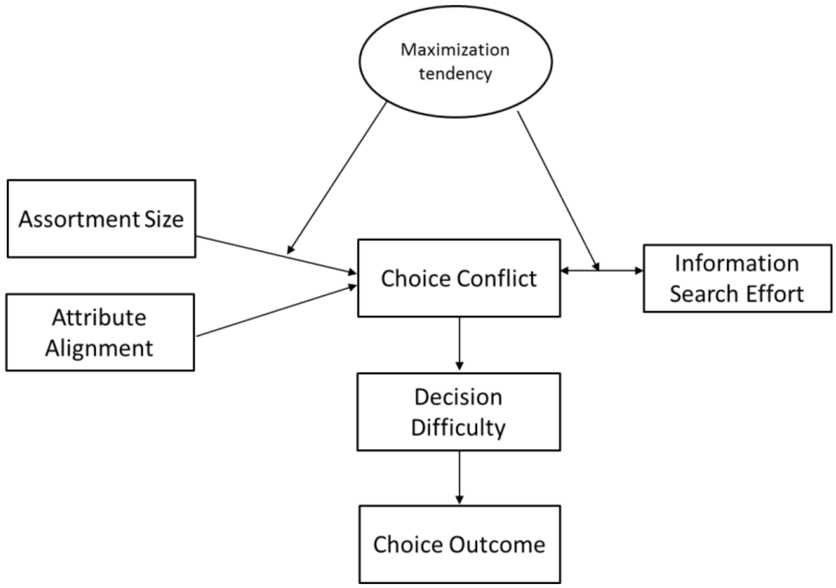

Figure 3 - Preliminary Research Model - Exploratory Study;
The arrows indicate the expected connections between constructs, based on review of the literature.

Because search for alternatives seems to increase the difficulty, we were interested in the factors that influence the intention to search for information.

In the literature, choice conflict was studied mostly in the context of consumer decision-making behavior, specific to the traditional offline environment where choice proliferation is relatively restricted by the cost of physical space (Anderson, 2006). Yet, little information exist on how choice conflict manifests and influences consumer decision-making behavior in the online environment, where available alternatives are virtually infinite. In order to close this gap, we propose to make an exploratory study of the online decision-making process in order to map similarities and differences between the two decision-making processes (the offline process derived from literature, and the online decision-making process which will be treated in the exploratory study). The exploratory preliminary research model is presented in figure 3.

The results of the exploratory study will provide the theoretical framework for simulating choice conflicts in a controlled, experimental way, which will allow us to draw causal inferences regarding the online shopping cart abandonment.

3. Exploratory Study

An exploratory research offers qualitative access to a broad variety of processes and situations while allowing methodological flexibility. Exploratory studies often result in observing new patterns and provide grounds for extending the knowledge about a phenomenon (Waters, 2007). These findings then form the basis for the inductive reasoning which help derive hypotheses to be tested.

3.1 Introduction

This exploratory study focused on observing the nature and sources of choice conflict and its frequency of occurrence in the online shopping context. It provided information on the online shopping process in general and detailed figures regarding the strategies used by consumers for solving choice conflicts, and showed which factors have an impact on exacerbating or reducing the difficulty of choice. The exploratory approach builds on the preliminary research mode (figure 3) adapted from the models of decision-making under choice conflict in the offline environment. Given the differences between the offline and online medium we expect that an exploratory study will provide arguments for extending the existing model towards the online decision-making under choice conflict.

3.2. Participants

Seventeen students at a Dutch University agreed to participate in the study, 9 males and 8 females, all between 21 and 36 years old (*M=24.24, SD=3.33*). The participants were familiar with the internet and shopping online as most of them made at least two online purchases each month. Each individual agreed to participate in the study and to have their verbal and video data recorded by signing an informed consent form. Participants were sampled on a voluntary basis using ads distributed mainly on the campus and on several university-related social networking groups.

3.3. Method and Procedure

Before starting the shopping task, the participants completed the Maximization Tendency Scale and reported on their online shopping frequency. Participants were also questioned on the extent of familiarity (i.e. previous knowledge or past experiences) with products from five categories: computers, mobile phones, digital cameras, household consumer electronics, and computer accessories.

We chose those categories because they are search-goods, that is they allow attribute evaluations before buying and consumption (Nelson, 1970), as long as the decision actors possess the knowledge to do so (Darby & Karni, 1973). In this respect such products are different from experience goods (i.e. travel packages) or credence goods (i.e. medical treatments) which cannot be evaluated before consumption, or without special knowledge and abilities (Galetzka, Verhoeven, & Pruyn, 2006).

Afterwards, each participant received the shopping task scenario and then was invited to use any webshops and take as much time as needed for performing the task. The scenario was identical and adapted for a product and a corresponding available budget for creating a shopping task. The shopping task was allocated based on the self-reported level of familiarity with that product category. In this respect we wanted to avoid assigning products with which participants were either very familiar, or not at all familiar. The reason for doing so was to balance the effect of product familiarity on choice difficulty (Luce et al., 2001; Scheibehenne et al., 2010). The distribution of the assigned task scenarios is presented in table 1.

Table 1

Distribution of Shopping Tasks Based on Familiarity with the Product Category

Shopping task	Available Budget a) (EUR)	N	%
Purchase a TV set	220	3	18
Purchase a Digital Photo Camera	140	6	35
Purchase a Laptop	550	5	29
Purchase a Mobile Phone	150	1	6
Purchase an Inkjet Printer	70	1	6
Purchase an External Hard-drive	110	1	6

Notes:
a) The available budget was established as the average price for the first 3 pages of results from amazon.com webshop in October 2015 for each product category. The products were sorted in ascending order ofprice

The participants followed freely the online shopping process until they decided to finish the process either by buying or abandoning. During the whole shopping session the participants were asked to think out loud.

After the shopping session was finished, the participants reported on the perceived decision difficulty, the satisfaction with the decision outcome, and on some demographic information. The full content of the questionnaires is presented in appendix A.

In debriefing, the participants were thanked and encouraged to comment on their experience during the study and on the perceived reality of the shopping scenario. All participants declared that the task was clear and realistic.

The think-aloud data together with the screen recordings, mouse events and questionnaire answers were collected from each participant using Morae Recorder (Techsmith Inc.). The study took place within the last week of May 2015 in the DemoLab within HMI Faculty of University of Twente.

3.4. Task scenario

One shopping scenario with adapted purchase tasks (product and budget, see table 1) was constructed for the exploratory study. The shopping scenario was designed to resemble as much as possible a real life shopping situation, in order to elicit authentic behavior (Nielsen, 2005).

To avoid providing clues or describing the required steps, the scenario gave the participants complete freedom to perform the shopping task. The available budget was pre-set at the category level, but participants had the freedom to decide to spend more/or less if they considered it worthy.

The scenario was not pre-tested, but the participants were asked to comment on the tasks, particularly if they encountered difficulties in understanding them, and on whether they perceived the purchase task as a real life situation (cf. Salvendy, 2012).

One participant made remarks on the pre-defined budget for the TV set purchase task, commenting that the budget was too small and decided to increase it. The full scenario and table of products/budgets is provided in appendix A.

3.5. Data analysis

The study resulted in seventeen case studies which amounts to 3.52 hours of audio-video recordings. Each shopping session data was analyzed and coded according to the think-aloud protocol (Ericsson & Simon, 1993), using the Morae Admin software package (Techsmith Inc.).

Analysis of the concurrent think-aloud protocols was done in two phases: data filtering and then axial coding for disentangling the constructs of interest (i.e. choice conflicts, information search, maximization tendency, assortment size, and decision difficulty) and the relations between them.

In the filtering phase we followed the exploratory research model to identify occurrences of key moments of the decision-making process, localizing it in time and providing a description of the situation. This resulted in a structural map of the observed episodes with a detailed view of each behavioral moment, its context and the relations between the involved constructs. The coding scheme is presented in appendix B.

3.6. Results

The focus of the data analysis was to discover the events and recorded actions that illustrate the choice conflicts and their possible causes in the online shopping environment and to document their frequency and impact on the shopping session. Subsequently, we investigated what happened when the participants reported conflicts. We were interested particularly in- the extent of information search undertaken to solve the choice conflict situations.

3.6.1. Participant characteristics

Twelve out of seventeen participants used three to five webshops during the shopping task (*n=12*). The shopping task duration was 6:30 minutes to around 30 minutes, with an average of 12 minutes (*M=12.42, SD=7,097*).

Twelve participants ended their task with a buying decision, four decided not to buy and one participant chose to buy but only for the sake of finishing the task. Thirteen participants considered less than five alternatives in their decision making and only two individuals evaluated more than eight alternatives.

Apart from five individuals, all others reported choice conflicts during the shopping session (n=12). The main reported source of conflict was difficulty to discriminate between the alternatives considered. To solve the conflict some participants engaged in extensive information search for finding arguments in support of trade-offs (i.e. choosing between options equally attractive, but in different attributes). In doing so, they became rapidly overloaded with information and the effort to process it added to the overall difficulty. For instance, nine participants searched the internet for product reviews and testimonials, made side-by-side comparisons, or searched for best buying tips, in order to decide between the considered alternatives. As a result, the decision making process was self-reported as difficult by most of the participants (*n=11*).

3.6.2. Online shopping process

The participants started the shopping task by finding and selecting a webshop; in doing so they relied on past knowledge or on the Google.com search engine. Three participants who were familiar with the Dutch ecommerce market used a webshop directory site to begin with the task (i.e. an online catalog for webshops).

3.6.2.1. Construction of the considered set

In the process of making decisions consumers restrict the space of all available options to a limited number of alternatives that are considered for value evaluation (Howard & Sheth, 1969). The restricted set of alternatives selected for evaluation forms the considered set. The considered set was built using a three-stage approach. First, participants used elimination by aspects (Tversky, 1972) to remove all the alternatives that are outside the given budget range. Next they used a lexicographic (Payne, Bettman, & Johnson, 1988) approach to decide which attributes are most important to consider. Last, they used elimination by aspect again to display only the alternatives which demonstrate acceptable levels for the selected attributes (e.g. show only products with 4GB of RAM and Intel i5 processor). Afterwards participants ordered the resulting products by price, first from lower to higher and then from higher to lower (note that the ordering took place inside the chosen budget). On average, participants included around four alternatives (M=3.94, SD=2.926) in the considered set.

The webpages with results were skimmed very fast for finding alternatives with interesting attributes: price, brand and design, color, and the like. If one alternative caught their attention, the participants opened it in a new browser tab and continued scanning on the main results page to find more products. This cycle was repeated until they got at least three alternatives in the considered set. The scanning process was on average very fast and superficial, lasting less than 30 seconds on each page of results. If there were no interesting products after the third page of results, the participants adjusted the shopping filter or reordered the product list instead of navigating deeper into the webshop structure.

3.6.2.2. Evaluation of alternatives

The participants inspected only the alternatives selected in the small considered set. The evaluation consisted in checking the attributes of each selected product. The decision to keep or reject an alternative was made by comparing the product attributes against a threshold based on past knowledge or common sense. If it failed to pass the threshold then the alternative was immediately rejected from the considered set. Take participant 8 for instance: she inspects some laptops and checks whether the microprocessor speed attribute passes a pre-set level (in the example the processor is an intel i5 with 2.7 GHz speed).

> **P8**-13:16: "[microprocessor] i-five, two point seven gigahertz… [noo], not good" [participant closes the browser tab]

Upon rejection of alternatives, the participants went back to the main page and searched for another product to complete the considered set. This behavior is interesting because it was expected that eliminating unwanted alternatives would make the online decision process simple and fast. Instead, participants preferred initially to have more options to choose from, expending some effort to search for more alternatives.

3.6.3.3. Assortment size. The number of available alternatives in the online environment

In general Amazon.com and Mediamarkt.nl were the preferred webshops for performing the shopping task. Because the online shops are using virtual shelves, there are practically no space restrictions for the products to offer. In this sense the number of choices for purchase online, at any time, is very large. Take for instance Amazon.com: in 2015 they had over 42 million electronic products in their offering (DataScraping, 2015); of this over 200.000 were digital photo cameras. All participants used the filtering tools provided by the webshops in order to restrict these huge choice space to a manageable size.

Apart from one who navigated more than five pages of results, all the other sixteen participants did not inspect more than the first third pages of results. Each webpage presented 24 alternatives, so, in general, the participants were exposed to a number of 70 to 100 products.

During the shopping session, the participants used an iterative process that can be described as follows: filter the available products, skim the results page, select any product that seems to fit the needs, go back and filter again. All participants did at least two iterative loops before starting the evaluation process. Therefore on average each participant was exposed to over 300 products per shopping session. In line with the bounded rationality theory (Simon, 1972), the participants considered only a small number of alternatives for evaluation. In this sense, the number of alternatives available on the webshop offerings (assortment size) did not play a role in the choice conflicts.

3.6.3. Choice conflicts

Based on the phases of the online decision making process in which choice conflict occurred, we observed two levels of choice conflict: superficial conflict and analytical conflict.

Superficial conflict happens when participants are scanning the online shop pages to select alternatives for in-depth evaluation. We observed that when scanning the webpages participants did not just randomly select some products for consideration. Instead, they seemed to make comparisons between some of the displayed products which attracted attention. This suggests the existence of a preliminary online decision making phase in which consumers compute the expected value based on apparent attributes (cues). A similar process was also observed by Ayal and Hochman (2009) who found that consumers select some options from a list of alternatives based on judgments. Consumers make the comparisons very fast, in less than ten seconds (Fiedler & Glöckner, 2012).and only between the alternatives that draw their attention (i.e. observed pupil dilatation and saccade-fixation-saccade on some alternatives noticed in the eye-tracking study of Fiedler and Glöckner, 2012).

Analytical conflict happens when consumers evaluate the selected alternatives and make in-depth attribute comparisons. In this process the participants usually viewed repeatedly the detail pages of each product, searched for information, reviews, and compared the levels of the attributes.

In conclusion, the exploratory study provided indications on the multidimensionality of the choice conflict concept when observed in the online environment. The superficial choice conflict is characteristic to environments where the number of available alternatives is very large and the cost of search and evaluation is low (Fiedler & Glöckner, 2012). For example webshops typically display the available alternatives in grid layouts and grouped in pages of results.

3.6.3. Sources of choice conflict

Most participants (n=12) experienced choice conflicts to some extent. Apart from some technical webshop errors encountered by one participant, the common source of conflict was difficulty to trade-off among desired attributes.

All participants in the study made comparisons between the alternatives present in the considered set after the second screening phase. In this process, twelve participants had to sacrifice some desirable attributes of one option against another. In cases where there were three or more options in the considered set, the trade-offs were more complex because they involved more deliberation. In the process of deliberation, the participants inspected repeatedly the pages with the alternatives most difficult to sacrifice.

For example see an excerpt of the verbatim data from participants 7 and 4:

> **P7**-10:02: "[participant describes one product attribute while investigating other alternatives] this seems better in stuff like more megapixels, more optical zoom [then looking back to the first product] less video resolution [OBS: participant gestures signal indecision and frustration] …shi…it's difficult to choose"

> **P4**-20:20: “ok so now I have like three laptops…the difference is not that big between them…I think I should compare maybe on some other site…”

Other observed or reported sources of conflicts were unavailability of the products, long delivery time, price comparisons or conflicts generated by improper search results (i.e. the participant searches for a product name and the webshop returns irrelevant results or no results at all).

Among all the purchase tasks, the digital camera (purchase task #2) and laptop (purchase task #3) elicited the most choice conflicts, accounted the most trade-offs between alternatives and took the longest time to complete (M=15 min, SD=10.48 min).

Therefore, the answer to the first exploratory research question,

$ExRQ_1$: “what are the sources of choice conflict in the online shopping environment” is consistent with the reviewed literature.

It seems that choice conflict stems from difficult trade-offs which mostly resulted from comparing alternatives on nonaligned attributes. Participants often reported the need to sacrifice one product better in some attributes for another which presented better but not dominant attributes. Apart from this main source, influences on the experienced choice conflicts were also observed in the lack of availability of some products, delayed delivery time, or technical errors of the medium (webshop).

3.6.4. Choice conflict frequency

In general, choice conflicts were experienced at least once by 12 out of 17 participants in the study (71%).

Any reported trade-offs between attributes was counted as a choice conflict. Moreover, the recorded indicators of intense deliberations between alternatives were also counted as a choice conflict (repeated inspection sequence of the same product pages, searching the internet for product x vs. product y, after inspecting each of them on the webshop, etc.).

Participants during the online shopping task encountered four conflicts on average (M=4, SD=2.523), while the maximum number of conflicts observed was 10 (n=1 participant), and five participants did not experience any conflict at all.

Participants who did not experience choice conflicts started the task not with a webshop but by using a comparison website (e.g. tweakers.net, beslist.nl, and the like). These websites gave the possibility to compare automatically thousands of products available on different webshops by specific attributes and budget set by the consumers. The results were then offered as a list with the best alternatives at the top. In this context the best means that products had the highest marks on the attributes defined by the participant, the lowest prices in the budget range, and also the best reviews (stars).

Take participant 10 for example. She configured the filters on the comparison website (beslist.nl) to match the purchase task and then selected the first option provided by the website and followed the hyperlink to one of the webshops that were offering the cheapest price and with which the participant had had previous experience. On the webshop she looked again at the attributes to make sure they matched the purchase task and the product she selected and then purchased the product. The whole shopping session lasted around 7 minutes.

Therefore, by using such comparison websites it seemed that these participants adopted a better strategy for decision making. These tools proved to be very helpful in taking away the burden of doing value evaluations between available options, making it easier to shop online. Nevertheless, not all the participants used these tools because they either did not know about them, or did not trust the claimed independence of these tools (participant 16 for instance declared that these websites are actually “manipulated by the big webshops who pay for having their products listed on top”).

We observed that such tools were useful for avoiding choice conflicts and decision difficulty. Therefore, we think that studying the acceptance, adoption and use of such online tools would be useful for understanding how the technology can improve the decision making process in online shopping.

However, considering that only three participants were using such tools (two other participants just selected the first option available and bought it) we consider that choice conflicts were commonly observed in most cases.

Therefore, also taking into account the average task duration of 12 minutes (M=12.42 min, SD=7.097 min), we can argue that choice conflicts occur relatively frequently online and appear to be influenced by the shopping duration, and the number of considered alternatives.

In this sense, the answer to the second exploratory question, *ExRQ*$_2$*: how often choice conflicts occur when shopping online*, is that for the majority of our respondents, choice conflicts occurred at least once, and their frequency increased with the time spent on task and the information search effort.

Additionally, if experienced choice conflicts increased in frequency, it was more likely for the participants to abandon the shopping session.

3.6.5. Resolving choice conflict

When confronted with the situation of trading one attractive alternative for another, the participants took two different routes.

On the one hand, 13 out of 17 participants took the satisficing approach (77%). They made a choice based on the alternatives present in the small considered set after the second evaluation phase. When encountering conflict, they inspected the same alternatives again and selected the first to pass a good enough threshold. In this context, good enough meant an option that fit within the pre-set budget, had some good reviews and was available for fast delivery.

On the other hand, four participants embarked on a maximizing behavior path. Firstly, they experienced choice conflicts from the initial evaluation phase. After comparing each alternative against the others, they started searching the internet for acquiring more information about the options already considered. In parallel they also searched for other possible alternatives, fearing they might miss a better one which ‘is somewhere out there”.

Take participant 11 for instance: she found a dominant alternative in the initial considered set of three possible options. Instead of choosing it she decided to look for more, just to be sure she will not miss an even better alternative.

> P11-10:57: “[hmm] ok this is definitely better than the Nikons…but yeah I would like to see the display…”
>
> P11-11:59: “ok that could be [pause] an option…let’s check further”
>
> P11-35:53: “ok, I don’t want to buy anything” [OBS: participant suddenly end the task]

In the search process she evaluated 13 alternatives, spent 25 minutes, and experienced 10 choice conflicts (trade-offs). In the end she decided not to buy anything and reported a very difficult decision process.

To sum up, the answer to the third exploratory question, *$ExRQ_3$: what consumers do to resolve a choice conflict when shopping online*, is that all participants tried to deal with the choice conflicts by engaging in collecting more relevant information online, to find arguments to lessen the trade-offs. In doing so, however, the participants adopted different paths and reached different solutions when trying to resolve the choice conflicts. The difference was found in the depth and breadth of the extra information search; some searched more and had harder time processing the new information, while others searched only until they established a satisfactory argument for solving the conflict. As expected, the participants who showed maximizing behavior got involved in an intensive search effort, while the adopters of a satisficing approach spent less search effort.

3.6.6. Information search effort

Participants engaged in both external and in-site search activities to gain information about the available alternatives online, and to find support for the decision process.

Part of the information search happened at the beginning of the shopping task when the participants were gaining knowledge about the available webshops, and/or products. However, most of the search was performed by the participants in trying to resolve a choice conflict.

In general the effort was expended to find and process reviews or other relevant information about the desired products.

Again a clear distinction could be made between the observed maximizing and satisficing *behavior*. The latter involved spending less effort for searching, and used the information so found only for providing arguments for a decision. The maximizing behavior meant spending observable effort in searching and processing large quantities of information. Moreover, this created more conflicts because, in the process of searching for information, the participants found other alternatives to be considered.

3.6.7. Maximization Tendency Scale

All the participants completed the Maximization Tendency Scale 9 item questionnaire which assess the maximizing tendency as a bipolar construct using five point Likert scale items, “No matter what it takes, I always try to choose the best thing”, (1 = strongly disagree, 5 = strongly agree). Although the sample used was very small, the scale maintains reliability (α=.754). The maximizing tendency was computed as a total score where higher scores means tendency to maximize and lower scores means tendency to satisfice (Highhouse et al., 2008). Most participants scored on average slightly above the mid point of the scale (*M=3.44, SD=0.606*) indicating a tendency to satisfice.

In conclusion, the Maximization Tendency Scale provided inconsistent information about the participants’ tendency to maximize the outcome of a decision-making process. Namely, one third of the participants manifested behavior associated in the literature with a high maximizing tendency, while their scores showed a tendency to satisfice. We think that this questions the unidimensionality of the maximizing tendency construct which states that one cannot be at the same time a maximizer and a satisficer. The following chapter will elaborate this issue.

3.6.8. Maximization behavior

As remarked in the previous chapter, there was no association between the maximizing tendency score and the actual maximization behavior. Recall that maximizing tendency should at least have an influence on the search effort if not also on the decision difficulty and decision deferral.

While all the four participants who abandoned the shopping cart manifested maximization behavior (i.e. searching extensively for finding the best product) there were no systematic differences between the participants in the scores on the maximizing tendency scale ($W=111.5$, $z=-0.624$, $p=.533$, ns.). These results indicate some conceptual aspects which raise doubts about the assumption of bipolarity of the maximizing tendency construct. The assumption states that individuals cannot be at the same time maximizers and manifest a satisficing behavior, and the other way round (Schwartz et al., 2002). However, our results indicate that some participants manifested a maximization behavior while their individual tendency was to satisfice, in line with (Rim et al., 2011). Therefore we recommend the Maximization Inventory scale developed by Turner et al. (2012) to be used in future research, as this measures the satisficing tendency separately.

In conclusion, we propose both maximizing tendency *and* maximization behavior to be considered in the experimental study because otherwise the results regarding the influence of maximizing tendency on the choice conflicts could be flawed.

3.6.9. Decision difficulty

Decision difficulty was assessed after the online shopping task with a single item question, “how difficult was it to make a decision between the alternatives available?”, measured on a 5 points semantic differential (1=very easy, 5=very difficult). On average, the participants reported the perceived difficulty of the decision process as neither easy, nor difficult, closer to the midpoint of the scale ($M=3.12$, $SD=0.993$).

Decision difficulty was observed to be influenced to some extent by the number of choice conflicts and usually participants experiencing a difficult decision process were also less satisfied with their decision. It seems that choice conflicts do amplify to some extent the perceived decision difficulty. Conversely, when more decision difficulty was experienced, the lesss satisfaction did the participants feel with their decision, suggesting a relation between satisfaction with the outcome and decision difficulty.

3.6.10. Decision outcome

Thirteen participants finished the shopping task with a buying decision, while only four decided to defer the choice and abandon the shopping session. The four participants who abandoned the session experienced on average more choice conflicts than the other participants ($M_{abandon}$=6.25, SD=2.986 vs. $M_{purchase}$=1.77, SD=1.787) and reported increased decision difficulty ($M_{abandon}$=4, SD=0.817 vs. $M_{purchase}$=2.84, SD=0.899). This suggests a possible link between experienced choice conflicts, perceived decision difficulty and shopping cart abandonment.

However, there seems to be no connection between shopping abandonment and the satisfaction with the decision made by the respondents. On average, all participants were satisfied with the decision made ($M_{abandon}$=4, SD=0.816 vs. $M_{purchase}$=4.31, SD=0.751, 5 points semantic differential, 1=very unsatisfied, 5=very satisfied). This indicates that the decision to abandon the shopping session was also considered satisfactory by the four participants.

3.7. Implications from the exploratory study. Extending the theoretical framework

The exploratory study findings provided grounds for extending the theoretical knowledge about choice conflicts in the online decision making envrionment. They will be developed in the following section.

Note: the section contains only the updated constructs and discussion resulting from the exploratory study; the rest of the concepts are described in the literature review (chapter 2).

3.7.1. Choice conflicts

The exploratory study revealed two levels of choice conflict: superficial conflict, specific to online environments, and analytical conflict. The analytical conflict represents the number of alternatives evaluations (measured as the number of accesses to product-details webpage).

The superficial conflict occurs when participants scanned the available products fast in order to choose some of them for later consideration.

3.7.2. Maximization behavior

We observed inconsistencies between maximization behavior and maximizing tendency measured as an individual trait, thus questioning the bipolarity of the construct (see chapter 3.6.8). All the participants who manifested maximizing behavior (i.e. searched extensively for finding the best product) experienced the most conflicts, spent the highest search effort to resolve them, perceived the shopping process as very difficult, and in the end abandoned the shopping cart. However, their scores on the Maximization Tendency Scale were not indicative of individuals with high maximizing tendency. Consequently, we expect that the goal to get the best product will trigger a maximization behavior, even though the consumer does not have a maximizing tendency.

3.7.2. Perceived decision difficulty

The results from the exploratory study were inconclusive in regard to the role of the choice conflicts in influencing the overall perceived decision difficulty. However, in the exploratory study we observed the relation between perceived decision difficulty and shopping abandonment ($r=.508$, $p=.037$), as expected from the literature review and illustrated in the preliminary research model (figure 1).

3.8. Limitations

For this exploratory study the main limitation derives from the small number of participants, which translates in reduced chances of capturing a very broad range of situations and cases. Another direct implication and limitation of the small sample used is the representativeness of the observed cases. We cannot assume, at any point, that the cases we observed are particularly representative for all maximizers for instance.

Nevertheless, the exploratory study did not lack methodological and procedural grounds. First, the study was built on top of a research model which provided guidance on what to observe during the research. Next, the data collection was based on the concurrent think-aloud procedures. Think-a-loud protocols are shown to yield valid observations in communication and human-media interaction research (Ericsson & Simon, 1993; Van den Haak, De Jong, & Schellens, 2003).

To sum up, the exploratory study offered a detailed view of the online decision making process in choice conflict situations. Additionally, it provided information about the observed sources of conflict, their frequency, and the behavioral patterns consumers adopt when confronted with choice conflict while shopping online.

4. Main study - Online shopping experiment

Choice conflict was observed to be a significant factor for decision defferal and abandonment in the offline world (Kahneman & Tversky, 1979; Luce et al., 2001; Shafir et al., 1993; Tversky & Shafir, 1992).

Building on the premise that choice conflict is playing a similar role in the online shopping environment we designed a controlled experiment for determining *to what extent choice conflicts influence the shopping cart abandonment rate in online shopping*.

4.1. Research model and experimental hypothesis

We investigated the causal relations between sources of conflict, solving strategies, and choice

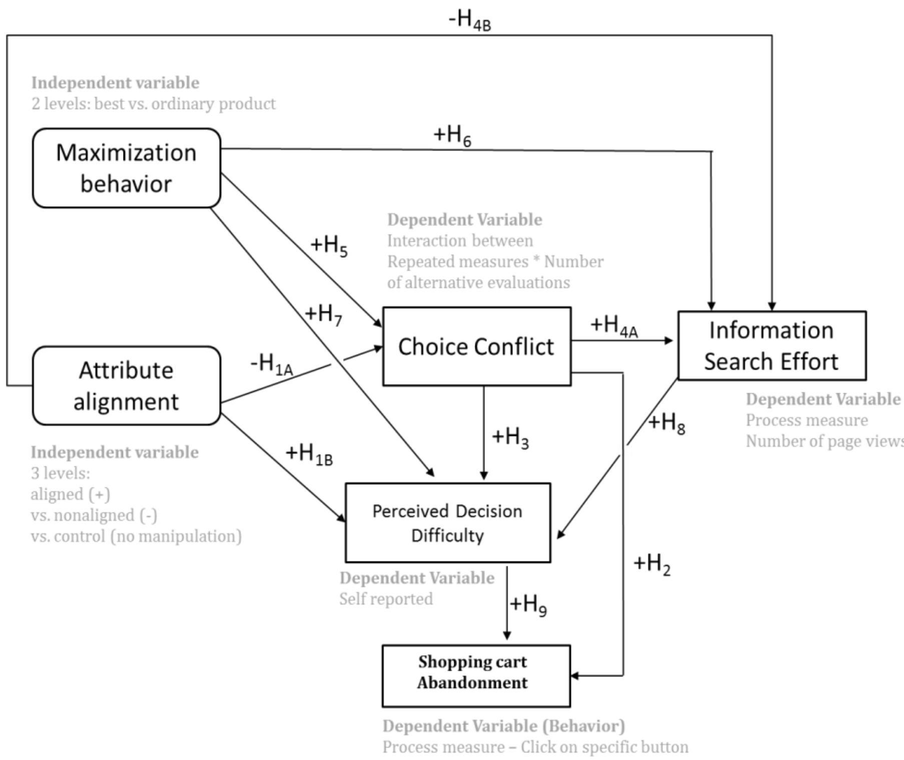

Figure 4 - Research Model adapted for studying choice conflict in online decision making. Main Experiment

conflict, for answering the overarching research question regarding the extent to which online shopping cart abandonment is influenced by the choice conflict.

To begin with, for testing whether alternatives with nonaligned attributes are causing choice conflict, we formulate the following hypothesis:

> ***H_{1A}**: when consumers compare alternatives with nonaligned attributes, they will experience more choice conflicts than if the alternatives have aligned attributes*

Subsequently we test the effect of attribute alignment on the perceived decision difficulty. We expect alternatives with nonaligned attributes should decrease the perceived decision difficulty in the online shopping medium. Therefore we hypothesize the following:

> ***H_{1B}****: when consumers compare alternatives with aligned attributes, they will perceive less decision difficulty than if the alternatives have nonaligned attributes*

In order to test the effect of choice conflicts on the online shopping cart abandonment we expect that higher number of conflicts will determine consumers to abandon the shopping cart. Thus the following hypothesis is formulated:

> ***H_2****: the higher the number of choice conflicts consumers experience, the greater the chance of abandoning the shopping session*

We also expect that experiencing choice conflicts could amplify the consumer's perceived decision difficulty with the overall shopping session. Therefore we propose the following hypothesis for testing whether consumers experiencing choice conflicts will in fact perceive a difficult decision making process:

> ***H_3****: the higher the number of choice conflicts consumers' experience, the higher the perceived decision difficulty will be*

Subsequently, when the participants in the exploratory study encountered choice conflicts, they started to gather more information about the alternatives under evaluation, in order to find support in deciding between them. In this respect we intend to check if consumers engage into searching for information in order to try and solve the choice conflicts. Additionally we expect that comparing products with nonaligned attributes will determine consumers to try to search for further information.

Therefore we formulate the following two hypotheses for answering those questions:

> ***H_{4A}****: the higher the number of choice conflicts consumers will experience, the more effort they will expend to search for information in an attempt to resolve the conflict*
>
> ***H_{4B}:*** *when consumers compare alternatives with nonaligned attributes, they will expend more effort searching for information than if the alternatives have aligned attributes*

In the main experiment we instructed participants to buy the best product in a manipulated task scenario to test whether consumers searching for the best products will experience more choice conflicts, more decision difficulty and whether they will spend more effort in searching for information. Thus:

H$_5$: *when consumers are instructed to buy the best product they will experience more choice conflicts than when they are not instructed to buy the best product*

H$_6$: *if consumers are instructed to buy the best product then they will expend more effort searching for information than if they are not instructed to buy the best product*

H$_7$: *if consumers are instructed to buy the best product, then they will perceive higher decision difficulty than if they are not instructed to buy the best product*

Next, for testing whether the effort of searching for information has an adverse effect byin increasing the perceived decision difficulty, we formulated the following hypothesis:

H$_8$: *the more information search effort consumers will expend, the higher the perceived decision difficulty*

Finally, we expected that not only choice conflicts, but also the perceived decision difficulty will determine consumers to abandon the shopping session. To test this hypothesis we formulated the following:

H$_9$: *the higher the perceived decision difficulty the higher the chance of abandoning the shopping session.*

To sum up, we formulated and tested a set of eleven hypotheses which represent the deducted causal relations embedded in the research model presented in figure 4.

4.2. Method and procedure

For the purpose of testing the hypotheses, an experimental online shopping study of 2 (best vs. a new product) by 3 (aligned vs. not-aligned attributes vs.control) between subjects factorial design was constructed.

Qualtrics survey tool (Qualtrics LLC.) was used for collecting self-reported data and for assigning participants randomly between conditions. For the shopping session a custom experimental webshop was designed, programmed and implemented. The products offered on the experimental webshop were real digital cameras provided by Amazon.com via their Product Advertising free API.

4.2.1. Participants

The sampling unit was any adult (age ≥ 18 years) who fulfilled the eligibility criterion: having made at least one online purchase in the last six months. The sampling method was convenience sampling, respondents selected themselves for participating in the main study.

The hyperlink to the experimental material together with a short description was distributed on social network sites, and online forums. The experiment was posted also on the University SONA pool (a platform for recruiting participants from undergraduates), students receiving 1 credit point for a complete contribution.

To attain a desired statistical power level of at least .80 while keeping the chance of committing Type I errors at the conventional 5% level (α=.05) and observing a medium effect size of at least .35 (Cohen, 2013), the minimum number of participants for each experimental condition was determined to be 25 (n = 150 participants in total, computed with G*Power software v.3.1.9.2, Franz-Faul, Kiel Univerity; effect size = .35, α=.05, 1-β=.95, J = 6, I=5, estimated actual power = .9513).

4.2.2. Random assignment procedure

Participants were randomly assigned to one of the experimental maximization behavior groups based on the shopping task (instructed to buy the best product vs. not instructed), using Qualtrics tools. Afterwards, participants were redirected to the experimental webshop designed to resemble the Amazon.com website. The website had implemented an algorithm for randomly assigning visitors on one of the three experimental attribute alignment conditions (aligned vs. nonaligned vs. control). The experimental design is presented in table 2.

Table 2

Main Study: Groups and Experimental Conditions

ID Condition	Maximization Behavior a)	Attribute Alignment b)
1.	+	+
2.	+	-
3.	-	+
4.	-	-
5.	+	0
6.	-	0

a) Levels: participants instructed for buying the best product (+); participants not instructed to buy the best products (-)
b) Attribute Alignment Levels: Aligned attributes differing on one dimension only (+); Nonaligned attributes differing randomly on all dimensions (-). No manipulation: the products are served exactly as they appear on Amazon.com product feed (0).

4.2.3. Task scenario

In the exploratory study shopping for photo cameras required on average the longest time to complete (*M=15m, SD=10.48m*) and elicited a wider spectrum of observations in the exploratory study. Therefore, we used digital cameras in the shopping task scenario for the experimental study.

The shopping scenario was: "Your plan is to buy (a new vs. the best) photo-camera from this website for under 300 Euro". The scenario informed participants that they could choose to buy any product that fits in the budget and preferences; also, as in real life, they could decide to increase the pre-set budget up to 340 Euros if they thought necessary. The complete task scenario is presented in appendix C.

4.2.4. Measuring choice conflicts

We used the following method adapted from Odekerken-Schröder and Wetzels (2003), to measure choice conflicts: the number of product evaluations weighted by the perceived decision difficulty during the shopping session.

We observed in the exploratory study that the difficulty to make a decision varied with the experienced superficial choice conflict. In other words, when consumers scanned fast the list of available products they reported difficulty making a decision. Hence, in the experimental study we used repeated measurements at fixed points in time for capturing and measuring a similar variation of decision difficulty during the shopping session. A single item question was used "up until now, how difficult has it been for you to choose one of the available alternatives" (7 points semantic differential, 1=very easy, 7=very difficult). The question was presented in a modal popup dialog which required user input to continue.

Using the recommendations from Chan et al. (2004) in order to maintain the efficacy of the popup method, the maximum number of popups per shopping session was restricted to 7. From the exploratory study we observed that a typical shopping session lasted around 15 minutes. As such, the repeated measures were made at constant time intervals of 2 minutes.

4.2.5. Measuring Maximizing Tendency

The findings of the exploratory study indicate that a maximizing tendency is not a unidimensional bipolar construct, tending to maximize at the upper end and satisfice at the lower. In the exploratory study we observed that participants manifested a maximization behavior while their individual maximizing tendency measured on the Maximization Tendency Scale (Highhouse et al., 2008) was to satisfice. This suggests that maximization and satisficing are two separate dimensions, in line with Rim et al. (2011). Therefore we used the Maximization Inventory scale developed by

Turner et al. (2012) in the main experiment, as this measures the satisficing tendency separately. the Maximization Inventory scale has 34 items which measure three subscales:

- Satisficing tendency (10 items, α=.73), i.e. "I usually try to find a couple of good options and then choose between them"
- Alternative search (12 items, α=.83), i.e. "I take the time to consider all alternatives before making a decision."
- Decision difficulty (12 items, α=.85), i.e. "I usually have a hard time making even simple decisions."

All items are 7 points Likert scales, "Strongly disagree-Strongly agree". The total score for maximizing tendency is computed as the summated score of decision difficulty and alternative search.

4.3. Experimental set-up

The main study consisted of three parts and complete participation required in completing all the parts.

In the first part, the participants were qualified and then randomly assigned to the shopping task scenario (buy a new vs. the best photo camera). Next, the participants were directed to the second part of the main study, the experimental webshop of "Ashop-x.com" which was built by the author specifically for this study.

In the second part, participants who landed on the webshop were randomly assigned to one of the three attribute alignment conditions: code 0 no-manipulation (control), manipulation code 1 (nonaligned attributes), and manipulation code 2 (aligned attributes). At any time during the task shopping the webshop provided participants with the possibility to review the shopping task scenario, together with some instructions regarding the procedural requirements. A detailed view on the instructions is presented in appendix C.

There were two possible outcomes of the experimental shopping task on the webshop: buying a product (resulting in a conversion), or deciding not to buy (resulting in abandon). These outcomes were implemented using two action buttons available on the webshop: the button "buy this product" for recording a conversion (a purchase), and the button "I decided not to buy" for recording an abandon. Clicking on either of these buttons ended the shopping session and the participants were redirected to the third part of the main study.

In the third part, the participants had to report the perceived decision difficulty of the shopping task, answer the Maximization Inventory questionnaire, and report on several other questions such as involvement with the photo cameras, decision satisfaction and the like (the full questionnaires are presented in appendix C).

4.3.1. Experimental manipulations

Three experimental conditions were constructed based on the attribute alignment experimental factor. The manipulations were constructed as follows:

a) In the nonaligned experimental condition, each product was served with different attribute levels from the one before as illustrated in figure 5;
b) In the aligned experimental condition, the system first randomly chose one attribute (e.g. the megapixel resolution) and then each product received different levels on that principal dimension, the rest remaining unchanged (see figure 6)
c) The third experimental condition involved showing the products as they were retrieved by amazon.com product feed. They were identical to the ones fund on the real amazon.com webshop

Figure 5 - Experimental Manipulations. Factor: Attribute alignment. Manipulation: nonaligned attribute. The picture illustrates an example of alternatives with nonaligned attributes. Alternative A has 20 megapixels, 3x optical zoom, and 2 inch LCD screen. Alternative B has 24 megapixels, 12x optical zoom, and 3 inch LCD Screen. Note: The legend and the color usage were not present in the real webshop. The battery-life attribute was available only on the product page.

Apart from the control condition, where product attributes were not manipulated at all, the levels for each attribute were allocated independently by the system from the levels presented in table 3.

Table 3

Levels Assignment Table for Manipulation of the Photo Camera Attributes

Attributes	Level 1	Level 2	Level 3	Level 4
Camera Resolution (MP)	12MP	16MP	20MP	24MP
Optical Zoom (X)	3x	5x	12x	20x
Battery Life (Photos/cycle)	150	300	400	600
LCD Screen size (Inch)	2”	2.5”	3”	3.5”

Figure 6 - Experimental Manipulations. Factor: Attribute alignment. Manipulation: aligned attribute. The picture illustrates a screenshot of the webshop. The alternatives were different on a single dimension – selected by the system randomly. In the example, the selected dimension was optical zoom. The other attributes were fixed to a randomly chosen level from the allocation table E2 and did not change. Alternative A has 16 megapixels, 12x optical zoom, and 3 inch LCD screen.
Alternative B has 16 megapixels, 3x optical zoom, and 3 inch LCD Screen (the LDC size is not visible in the title for alternative B but was available on the product page). Note: The legend and the color usage were not present in the real webshop. The battery-life attribute was available only on the product page.

4.3.2. Experimental webshop

The experimental webshop was designed to resemble the look and feel of the Amazon.com website because amazon.com is a worldwide big online shop with an average of 1 billion visitors each month. Therefore, it was expected that emulating amazon.com would give the look and feel of a real webshop to the experimental website. The webshop was populated with products related to digital cameras imported directly from amazon.com products feed. All the products used in the experimental webshop were real, with the real prices, attributes, product descriptions, and images. Participants had the possibility to filter the product feed by Brand and by Price. Also they were able to list the products by price (low-high, high-low).

Similar to the real webshop (amazon.com) they were shown a matrix layout of three products per row, ten products per page (due to a restriction imposed by the feed system only 10 products per page could be imported at a single query). A screenshot of the actual results page is presented in figure 7.

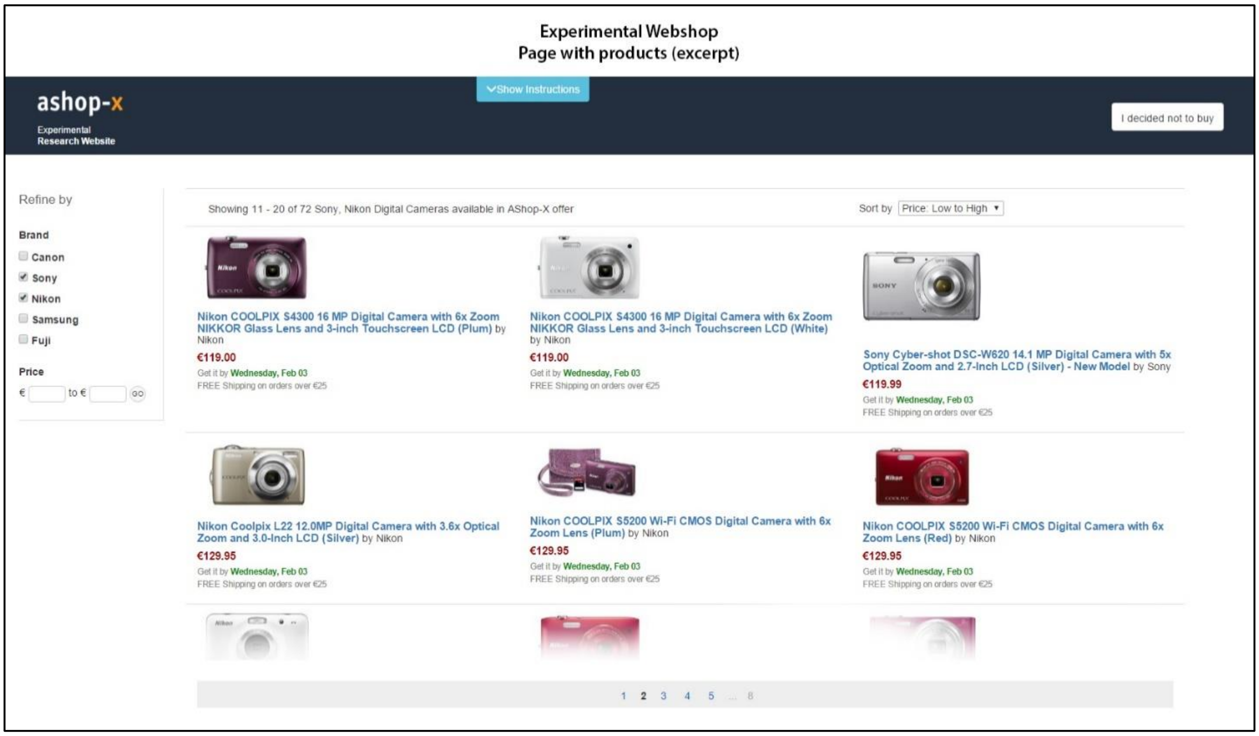

Figure 7 - Experimental webshop example. The products are displayed in a 3x3 grid. The screenshot was cut for displaying reasons.

Clicking on the product link or image opened that product details on a dedicated page (figure 8). Here the product attributes, features, description and a gallery of product images could be inspected in detail. Participants could buy that product by clicking on “Buy this product” button or navigate back to the main results page. Also they had the possibility to abandon the shopping session by clicking the “Decided not to buy” button present on the top-right side of each page.

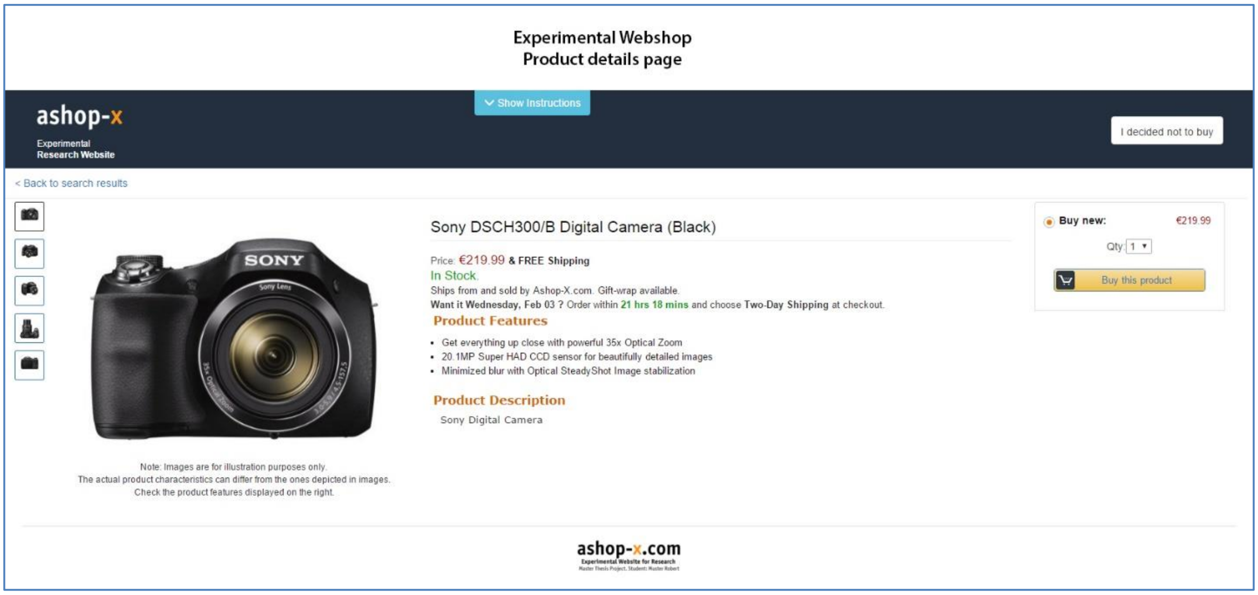

Figure 8 - Experimental webshop screenshot. The picture illustrate the product details page. Participants can decide to buy/abandon the shopping session, view pictures and inspect the product attributes and description. To navigate back participants could click on the Back to search results link (on the top left side).

During the shopping session, the participant was questioned about the experienced decision difficulty by using a modal popup dialog which required the user input to continue. The question was presented at equal intervals of two minutes for a maximum seven times. The popup is presented in figure 9.

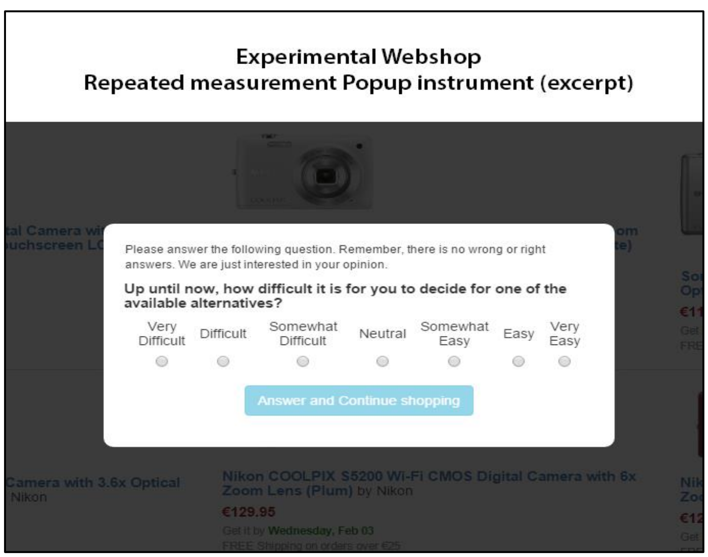

Figure 9 - Experimental webshop screenshot. The picture illustrates the popup for measuring the variation of experienced difficulty. Participants had to answer the question in order to continue. The popup was served at fixed intervals of 2 minutes during the shopping session (the timer was paused while the popup was visible). Note: the item scale (1-7) is displayed in reversed order to prevent answers on “auto-pilot” (Chan, Dodd, & Stevens, 2004). The background was dimmed while the popup was displayed to avoid distracting the participants.

4.4. Special measurement instruments - Mouse tracking

We collected the mouse data using a script (Mousestats.com) which video-recorded all the browsing activity together with the mouse events (i.e. move, click, scroll, select text, enter input, page change, and the like).

Research has shown that mouse-movements are correlated to some extent with eye-gazing captured in eye-tracking studies (Navalpakkam & Churchill, 2012; Rodden, Fu, Aula, & Spiro, 2008). They show that the mouse cursor was used as a focusing tool – e.g. the mouse followed gazing horizontally and diagonally when user read a block of text. Similar, users selected parts of text which they considered important to focus on.

In general, mouse-tracking data were considered valid indicators of dynamic, real-time cognitive processes (Hehman, Stolier, & Freeman, 2015). For instance, Joachims, Granka, Pan, Hembrooke, and Gay (2005) found that clickstream data provide reasonable accuracy for deducting user decision to click on a link from the mouse-tracking data. They concluded that clicks are "pairwise preference statements", (p. 6), meaning that clicks are not absolute indicators of judgements but are relative indicators of preference: users choose what to click as opposed to what not to click. Hence, they state that a click on A from a set including [A, B, C] indicates an underlying evaluation process (i.e. user clicked on A because A was considered against B and C).

Therefore, we argue that mouse-tracking data should be used to supplement the quantitative findings, especially by providing an unobtrusive method to observe use-cases. We used mouse-tracking to see what participants actually did during the shopping session.

5. Results

The results section provides the empirical data support on which we can build the discussion about the role of choice conflicts in the online decision making process. The analysis focused mainly on testing the hypothesized relations between choice conflict, its sources and its effects on the way consumers make decisions when shopping online. The objective was to check whether there is enough supporting evidence to enable an alternative explanation to the high rates of shopping cart abandonment which are reported in the ecommerce industry. The data analysis is mainly quantitative and was performed using SPSS Statistics 21 (IBM Inc.). The mouse-tracking data were inspected, when needed, using the Mousestats.com analysis dashboard.

5.1. Pretest and manipulations check

The experimental webshop and experimental manipulations were checked prior the main data collection. Ten participants, four males and six females, selected at convenience from a social network site were willing to participate in the pretest. Two participants did not complete the whole experiment and were removed from the data.

Eight participants started the experiment by answering the first questionnaire and received the shopping task. The participants were split equally between the task scenarios (buy the best vs. a new photo camera) and then were redirected to the experimental webshop (see table 4).

Table 4

Participant assignment between groups and experimental conditions - Pretest

	Control	Not Aligned	Aligned
	N	N	N
Shopping task scenario			
Ordinary product (N=4)	2	1	1
The best product (N=4)	0	2	2

To check whether instructing participants to buy the best was salient enough to trigger a maximization behavior, the following variables were investigated: number of alternatives inspected, time-on-task, perceived decision difficulty and the maximization inventory subscales.

The participants who received the instruction to buy the best product were expected to spend more time on task, inspect more alternatives and to perceive higher decision difficulty, compared to the ones not instructed to buy the best product.

Table 5

Participant Characteristics - Manipulation Checks (summarized results)

	Instructed to buy the best photo camera		vs.	Not instructed to buy the best photo camera	
	M	SD		M	SD
Time on task (minutes)	22.5	13.178		9.5	4.509
Perceived decision difficulty	5.00	1.414		3.75	0.957
Number of inspected alternatives	4.75	3.304		3.25	1.5
Maximizing tendency a)	4.68	0.598		4.44	0.946
Satisficing scale b)	5.97	0.210		5.97	0.630
Involvement with the photo camera c)	3.92	0.918		3.58	1.101

Notes:
The first three rows confirm the expectation that participants instructed to buy the best product will spend more time on task and inspect more alternatives while perceiving higher decision difficulty, than the ones not so instructed. However, it was important to check for involvement and the participants' tendency for maximizing or satisficing in order to make sure that the differences are generated by the instruction to get the best product and not from something else.
a) Maximization Inventory scale items were 7 points Likert scales, 1=strongly disagree, 7=strongly agree; Maximizing tendency score is summated from alternative search and decision difficulty subscales
b) Satisficing is a subscale of Maximization Inventory scale
c) Product involvement, summated 3 item scale (7 points Likert scale, α=.80) – adapted from Product Class Involvement (Bearden & Netemeyer, 1999)

Although the sample used was small, we were able to draw a conclusion about the effect of the shopping task. In order to make sure that the two groups were comparable in terms of their maximization tendency (as an individual trait) we compared the results on the Maximization Inventory scale. From table 5 it is evident that the two groups score similarly in their total score for maximizing tendency, satisficing tendency and product involvement, thus the differences observed in the way the respondents approached the shopping task were not due to a pre-existing tendency to maximize (or satisfice).

It seems that the instruction to buy the best photo camera was effective in triggering the maximization behavior. Participants instructed to buy the best product spent twice as much time in minutes on the webshop (M_{Primed}=22.5, SD=13.178 vs. $M_{not\text{-}Primed}$=9.5, SD=4.509), investigated around five alternatives on average (M_{Primed}=4.75, SD=3.304 vs. $M_{not\text{-}Primed}$=3.25, SD=1.5) and perceived decision somewhat difficult while the other group were more inclined towards the middle point of the scale (M_{Primed}=5, SD=1.414 vs. $M_{not\text{-}Primed}$=3.75, SD=0.957).

We also approached one participant and asked her to comment on whether she noticed the differences between manipulations and whether the website gave the impression of a webshop.

We showed this participant all the manipulations for the attribute alignment factor and asked her to comment on them.

Based on the pretest feedback and conclusions we improved the shopping scenario by focusing on the shopping task rather than the context of the task. Also, we decided to make more salient the instruction to buy the best product by adding "best *possible*" in the task text. Some minor bugs of the webshop were also discovered and corrected during the pretest.

All things considered, we started the main data collection in the second week of November 2015.

5.2. Participants and experimental groups characteristics

A total number of 263 participants started the experiment, of which 25 were not qualified (they had not made any purchase in the last six months) and 196 finished (82% completion rate). Additionally, visits on the website of under two minutes were considered not valid and were excluded from the data analysis ($N_{excluded}$ = 32 participants).

The resulting 164 valid responses were collected and analyzed. After the qualification questions and some other demographic measurements, participants were randomly assigned to one of the two main shopping task scenarios ($N_{Not\text{-}Instructed}$=81, $N_{Maximization\text{-}Instructed}$=83), instructed vs. not-instructed for maximization, and then redirected to the experimental webshop.

We considered the participants instructed explicitly to buy "the best possible" photo camera as the group primed for maximization behavior. Chartrand and Bargh (1996) showed that explicit task instructions trigger similar behavioral response patterns as priming (i.e. nonconscious activation of user intentions and goals in response to the environmental context). Therefore we named the group receiving the instruction to buy the best possible photo camera as "primed for maximization"; the participants instructed to buy "a new" photo camera were considered as not primed for maximization behavior, hence we named them the "not-primed for maximization" group. The distribution of participants between experimental conditions is described in table 6.

Table 6

Participant Assignment Between Groups and Experimental Conditions – Main Experiment

	Control		Not Aligned		Aligned	
Shopping task Scenario Groups	N	%	N	%	N	%
Not primed for maximization	29	51%	27	50%	25	49%
Primed for maximization (to buy the best possible product)	28	49%	27	50%	28	51%

Over half of the participants in the sample were females (N=97, 59%); most participants were between 18 and 31 years old (M=25.13, SD=6.956). Consistent with the age group, the majority were high-school or university graduates (bachelor or master level). In general, the participants were frequent online shoppers, with nearly two-thirds of them shopping online up to three times a month.

Most participants (N=103) had not searched recently for information about photo cameras. Nevertheless, all of them had at least one preferred brand for digital photo cameras, and were confident in their ability to purchase a digital photo camera online ($M_{confidence}$=5.1, SD=1.602). The general demographic data can be inspected in table 7.

Table 7

Sample Demographics, Online Shopping Experience, and Product Class Knowledge

Demographics	N	%
Age [a)]		
18 to 24	91	58%
25 to 31	44	28%
32 to 38	13	8%
Over 39 years	8	5%
Education		
Primary school	1	0.6%
High school	81	49%
Bachelor level	55	34%
Master level	23	14%
PhD or PostDoc level	4	2%
Gender		
Females	97	59%
Males	67	41%

Online shopping experience	N	%
Shopping frequency		
Less than once a month	58	35%
Once a month	61	37%
2-3 times per month	36	22%
4-5 times per month	7	4%
More than 5 times a month	2	1%
Product class knowledge		
Photo Camera Interest in the last months [b)]		
Never	103	63%
Sometimes	50	30%
Often	11	7%
Photo Camera Brand preferences		
No brand preferences	58	35%
Some brand preferences	40	24%
Strong brand preferences	66	41%

Notes:
a) Self-reported on a scale from 18 to 100. Four participants did not declare their age.
b) Self-reported on a 5 points semantic differential (never-very often). The levels were aggregated

Because product class knowledge was found to influence the perceived decision difficulty (Bettman & Park, 1980) we considered this factor in data analysis. The data show that in general participants were familiar with photo cameras, having at least some preferred photo camera brands (n=106 participants). Additionally, no significant differences were found for product class knowledge (*t(158.36)*=1.047, *p*=.297, ns.), or on participants confidence in the ability to purchase a digital camera online (*t(162)*=-0.088, *p*=.930, ns.) between the participants primed and the ones not primed for maximization behavior.

In some studies product involvement was found to influence the decision making process (Botti & Hsee, 2010) and information search effort (Moorthy, Ratchford, & Talukdar, 1997). Hence, we also measured product involvement using Involvement with a Product Class scale (Bearden & Netemeyer, 1999) consisting on three 7-points Likert scale items (i.e. “Photo cameras are very important to me”) summated scale (α=.80 in the original study, α=.913 in the present study). The items are presented in appendix C.

The data revealed that on average participants scored relatively low in involvement with photo cameras (*M*=3.97, *SD*=1.621), the values clustering around the middle point of the scale (see table 8). There were no significant differences of consumer involvement with the photo camera between the instructed vs not instructed for maximization (e.g. buy the best) groups (*t(162)*=1.759, *p*=.081, ns.).

Table 8

Participant Characteristics for Possible Sources of Bias of the Main Study Findings

	Scenario Overall		Control		Not Aligned		Aligned	
Shopping Scenario	M	SD	M	SD	M	SD	M	SD
Primed for maximization behavior (instructed to buy the best possible photo camera)								
Maximizing tendency score [a)]	4.68	0.795	4.86	0.871	4.64	0.717	4.54	0.781
Satisficing scale [b)]	5.74	0.562	5.89	0.569	5.60	0.592	5.75	0.503
Involvement with the photo camera [c)]	3.49	1.721	3.32	1.623	3.52	1.939	3.64	1.638
Confidence in the ability to purchase a photo camera [d)]	5.11	1.530	5.11	1.548	5.07	1.542	5.14	1.557
Not primed for maximization								
Maximizing tendency score	4.66	0.711	4,60	0.707	4.70	0.762	4.69	0.684
Satisficing scale	5.70	0.599	5.82	0.506	5.64	0.672	5.61	0.615
Involvement with the photo camera	3.98	1.647	4.03	1.767	4.02	1.572	3.86	1.643
Confidence in the ability to purchase a photo camera	5.09	1.682	5.14	1.885	5.19	1.570	4.92	1.605

Notes:
a) Maximizing tendency score is summated from alternative search and decision difficulty subscales
b) Satisficing scale separate dimension from Maximization Inventory; 9 items 7 points Likert scales; α=.711
c) Product class involvement; 3 items 7 points Likert scales; α=.913
d) Single item; 7 points Likert scales

Nevertheless, because involvement is an important factor in the decision making process we decided to run separately a two-way ANOVA to check also for the interaction effect of involvement and experimental conditions. The test results confirmed that there were no significant differences in product involvement between the randomly assigned participants (F_{Task}=3.209, p=.075, ns; $F_{Alignment}$=0.045, p=.956, ns; $F_{Interaction}$=0.292; p=.747, ns).

In conclusion, the groups were comparable with regard to other variables that could influence and bias the decision making process, information search effort, or online shopping process. We had no reasons to suspect that the data analysis would be affected by the influence of these factors (see table 8 for the means and standard deviations of the scores).

5.3. Choice conflicts and the online decision making

In this block we focused on studying the choice conflicts in the online environment for finding answers to the questions regarding the role of choice conflicts in the online shopping abandonment. We introduce this chapter by discussing first the descriptives regarding the choice conflicts from our data.

All participants had to deal with at least 2 choice conflicts, wheras on average most of them experienced around 14 choice conflicts (M=13.98, SD=11.645).

Participants primed for maximization behavior experienced on average around 16 choice conlicts while the ones not priemd for maximziation experienced around 13 choice conflicts on average (M_{primed}=15.46, SD=14.128 vs. $M_{not\text{-}primed}$=12.45, SD=8.192).

It seems that under the non-aligned attributes condition participants experienced fewer choice conflicts (M=12.01, SD=9.481) compared to the the control condition (M=14.79, SD=13.057). Surprisingly, participants receiving the products aligned on a single attribute experienced the most choice conflicts compared to any other two groups (M=15.10, SD=11.994).

5.3.1. What causes choice conflicts while shopping online?

We predicted that when consumers compare alternatives with nonaligned attributes, they will experience more choice conflicts than if the alternatives have aligned attributes (H_{1A}). However, the data show no support for this prediction. Attribute alignment was not a significant predictor for the choice conflicts (Wald χ^2=3.683, p=.159, ns).

In spite of this result, we investigated further the effect of the attribute alignment levels on the choice conflict in order to check the role of attribute alignment in causing the choice conflicts. We found that the nonaligned attributes *seem to reduce* the number of choice conflicts by almost

21% as compared to the aligned attributes condition (β=-0.229, 1-exp(β)=0.205, $p=.081$, ns). A similar but weaker effect was observed between nonaligned and the control condition (i.e. representing products exactly as on the real amazon.com), reducing choice conflicts by only 2.1% (β=-0.021, 1-exp(β)=0.021, $p=.867$, ns).

Surprisingly, it seems that in the online environment if the products are displayed with attributes aligned on a single dimension the number of choice conflicts was 5 times higher than in the other two conditions (even though the effect was not significant). The coefficients are presented in table 9.

The statistical model used to draw the conclusions was a quasi-poisson linear model with tweedie log link for controlling the overdisperssion of the dependent variable. The statistical model assumption checks and other statistical methods for assuring the quality of the analysis are presented in appendix D. The model goodness-of-fit was assessed with the Akaike's information criterion coefficient (AIC=1181.770). The higher value indicates a low model fit to complexity ratio, indicating that the model might not include all the predictors for explaining the changes in the response variable.

In conclusion, we could not provide a clear answer regarding the contribution of attribute alignment as a source for choice conflicts. The attribute alingment seems to have an effect but because it was found not significant we argue that it is not the main source of choice conflicts in online shopping.

Another plausible source for choice conflicts might be the maximization behavioral approach of the shopping task (buy the best possible photo camera). We expected that participants who were primed for maximization behavior (i.e. to buy the best possible photo camera) would also experience more choice conflicts than the other group. Therefore, we tested whether when consumers were instructed to buy the best product they would experience more choice conflicts than when they did not receive this instruction (H_5).

We found that consumers primed for maximization (i.e. instructed to buy the best possible photo camera) experienced more choice conflicts than otherwise. The task scenario priming participants to adopt a maximization behavior had a significant effect on the choice conflicts experienced while shopping for the best possible photo camera (Wald $\chi^2=4.228$, $p=.040$). Therefore the data supported the hypothesis (see table 9).

Participants instructed to buy the best possible camera experienced on average around 16 choice conflicts (Exp(2.738)=15.460, p<.001). Participants who were not instructed to buy the best photo camera (i.e. buy a new photo camera) experienced 20% fewer choice conflicts than those going for the best product. On average, participants experienced 80% more choice conflicts when they had to buy the best possible photo camera than those who had the task to buy a new photo camera.

Table 9

Results Summary for Sources of Choice Conflicts: attribute alignment, and task priming for maximization behavior

	Wald χ^2	β	Exp(β)
Predictor Attribute Alignment			
Aligned (Intercept)	898.680	2.715**	15.102
Control	0.028	-0.021	0.979
Nonaligned	3.040	-0.229*	0.795
Predictor Task Priming for Maximization Behavior			
Primed for maximization (Intercept)	1452.301	2.738**	15.460
Not primed for maximization	4.228	-0.216**	0.806

Notes:
* Coefficient is significant at α=.10, p<.10
** Coefficient is significant at α=.05, p<.05

The statistical model used to draw the conclusions was a quasi-poisson linear model with tweedie log link for controlling the overdisperssion of the dependent variable choice conflicts. The model goodness-of-fit was assessed with the Akaike's information criterion coefficient (AIC=1179.235). Based on the data analysis we state that the desire to get the best product while shopping online is not the best strategy if one wants to avoid choice conflicts.

To sum up, it seems that attribute alignment is not influencing significantly the number of choice conflicts experienced while shopping online. However, the desire to get the best possible product does have a strong effect on the number of choice conflicts consumers will experience while shopping online for the best product.

5.3.2. What is the effect of choice conflicts on the online shopping abandonment?

We observed that of all the 164 participants, the majority decided to purchase a digital photo camera from the experimental webshop (N=143), and only 21 participants decided to abandon (13%).

The main objective of the present research project was to find to what extent choice conflicts influence the decision to abandon the online shopping.

We investigated whether higher choice conflicts determined those 21 participants to abandon the shopping task. It was expected that the higher the number of choice conflicts consumers experience online, the greater the chance of abandoning the shopping session (H_2). Nevertheless, the data show no support for this relation**.** It seems that choice conflicts are not directly influencing the chance of online shopping abandonment (Wald χ^2=0.871, *p*=.351, ns).

We inspected further the statistical coefficients because they can provide some indications on the direction and strength of the effects. Therefore, we examined the effect of the choice conflicts on the abandonment rate. The coefficients show that with each additional choice conflict a consumer experiences while shopping online, the odds of finalizing the purchase decrease by 2.4% (β=-0.024, 1-exp(β)=0.024, p=.351, ns). Although the statistical test showed not a significant result for the influence of choice conflicts on the decision to abandon the shop, it can be stipulated that lowering choice conflicts would increase the probability of a conversion by 39% (using the reverse logistic transformation). The coefficients are summarized in table 10.

Table 10

Results Summary for the Effect of Choice Conflicts on Shopping Abandonment

	Wald χ^2	β	Exp(β)
Predictor Choice Conflicts			
Intercept	17.016	-1.606**	0.201
Choice Conflicts	0.871	-0.024	0.976

Notes:
** Coefficient is significant at α=.05, p<.05

The statistical model used to draw the conclusions was a binary logistic linear model with logit link because the response variable was binary (1/0, 1=buy, 0=abandon).

The model goodness-of-fit was assessed with the Akaike's information criterion coefficient (AIC=78.793). The value shows a moderate goodness-of-fit to complexity ratio, indicating that the model was not able to explain the variation in the response variable.

In conclusion we did not find support for a direct effect of choice conflicts on the decision to abandon the shopping cart.

5.3.3. What is the effect of choice conflicts on the perceived decision difficulty?

We found in the exploratory study that experiencing more choice conflicts leads to higher perceived decision diffculty. To check this relation we investigated the data from the experimental main study.

In the main study participants perceived the decision process as neither difficult nor easy, the average decsison difficulty being relatively close to the mid-point of the 7 points Likert scale (M=4.41, SD=1.643). The correlation analysis showed a significant positive relation between choice conflicts and perceived difficulty (r=.218, p=.005). Therefore we had reasons to expect that the higher the number of choice conflicts consumers experience, the higher the perceived decision difficulty will be (H_3). The data showed support for stating that choice conflicts have a significant effect on the perceived difficulty (Wald $\chi^2=8.437$, $p=.004$).

We investigated further the parameter estimates and we argue that when the number of choice conflicts increases by one, the chance of experiencing a *very difficult* decision increases by 103.6% (β=.035, exp(β)=1.036, p=.004). It appears that the chance of perceiving the decision difficulty as *difficult* (sixth point on the Likert scale) is 17 times higher than the chance of perceiving extreme decision difficulties (β=2.871, exp(β)=17.66, p<.001). This means that, basically, most consumers perceived the decision process as difficult, and only some of them experienced it as high difficulty. This is a very important finding because it highlights the severity of choice conflicts contribution in influencing the perceived decision difficulty during an online shopping session (see table 11).

Table 11

Results Summary for the Effect of Choice Conflicts on Perceived Decision Difficulty

	Wald χ^2	β	Exp(β)
Predictor Choice Conflicts;			
Dependent variable: Perceived decision difficulty. Threshold = Very difficult [a)]			
Very easy	41.779	-2.844 **	0.058
Easy	24.796	-1.325**	0.266
Somewhat easy	0.567	-0.171	0.843
Neither easy, nor Difficult	0.784	-0.200	1.221
Somewhat difficult	32.101	1.433**	4.191
Difficult	68.699	2.871**	17.660
Choice Conflicts	8.437	0.035**	1.036

Notes:
a) The Generalized linear model with ordinal response variable uses the highest level of the dependent variable compared to the threshold. The coefficients therefore are computed in reference to the threshold level.
** Coefficient is significant at α=.001, p<.001

Moreover, we found that experiencing a choice conflict during shopping online raised the perceived decision difficulty by a factor of 9 to 35 times: 95%CI(β)=(8.956, 34.822).

The statistical model used to draw the conclusions was a ordinal logistic linear model because the response variable contained ordinal data. The model goodness-of-fit was assessed with the Akaike's information criterion coefficient (AIC=383.403). The value shows a moderate goodness of fit to complexity ratio, indicating that the model is not including all the explanatory variables to capture all the change in the response variable.

In conclusion, we found support for a direct and strong effect of choice conflicts on the perceived decision difficulty; the more choice conflicts consumers experienced the more difficult they perceived the shopping session to be.

5.3.4. What is the effect of choice conflicts on the information search effort?

We posited that the higher the number of choice conflicts consumers will experience, the more effort they will expend to search for information in an attempt to solve the conflicts (H_{4A}). The data show support for the relation between choice conflict and information search effort. Namely, choice conflicts have a main effect on the information search effort (Wald χ^2=298.821, p<.001). The results confirm the hypothesis that when consumers experience choice conflicts they will engage into information search as a strategy to solve the conflict.

The parameter estimates show that when consumers experienced more choice conflicts the search for information increased by 103.6% (β=0.035, exp(β)=1.036, p<.001). The coefficients revealed that participants viewed on average around two pages of information when experiencing a choice conflict (Exp(0.449+0.035)=1.623 pages/session). Additionally, with each extra choice conflict respondents doubled their search effort on the webshop (1.623 + 103.6%=3.304 pages/session, see table 12).

Table 12

Results Summary for the Effect of Choice Conflicts on Information Search Effort

	Wald χ^2	β	Exp(β)
Predictor Choice Conflicts			
Intercept	45.885	0.449**	1.567
Choice Conflicts	298.821	0.035**	1.032

Notes:
** Coefficient is significant at α=.001, p<.001

The statistical model used to draw the conclusions was a poisson linear model with log link because the response variable contained count data (number of pages accessed). The dependent variable presented low overdisperssion which did not raise model validity concerns. The methods used to ensure validity of the regression model are presented in appendix D).

The model goodness-of-fit was assessed with Akaike's information criterion coefficient (AIC=527.631). The values show a moderate goodness of fit to complexity ratio which means that the model is appropriate for explainign the changes in the information search effort.

In effect, we found support for the relation between choice conflicts and information search effort; experiencing choice conflicts leads to spending more effort in searching for information.

5.4. Perceived decision difficulty and the online decision making process

In this section we focused on the analysis of perceived decision difficulty in order to understand what could be another source of it, and how it affects shopping abandonment or the information search effort. Subsequently we investigated ways to reduce the perceived decision difficulty in order to improve the decision making process.

To begin with, on average, the participants perceived a somewhat difficult decision process, slightly above the middle point of the 7 points item (M=4.41, SD=1.643).

There were no significant differences between the difficulty perceived by the participants primed for maximization behavior and the ones not primed (t(162)=0.609, p=.544, ns). It seems that shopping for the best product din not influence consumers in perceiving a more difficult decision process. Therefore we state that there was no support for the assumption that consumers instructed to buy the best product perceived higher decision difficulty than those not instructed to buy the best product (H_7). In this respect, the data provided no basis for the relation between the desire to buy the best and the perceived decision difficulty.

We similarly investigated the relation between maximizing tendency as an individual trait and the perceived decision difficulty. The correlational analysis did not provide support for the relation between the tendency for maximizing the outcome and the perceived decission difficulty (r=.052, p=,505, ns). Also, perceived decision difficulty was not influenced by the individual pre-exisitng tendency for difficult decisions, measured as a subscale of the Maximization Inventory scale (r=.089, p=.257, ns).

These results indicate that whatever decision difficulty participants perceived during shopping online, it was due to the shopping session itself and not due to a pre-existing tendency for decision difficulty.

5.4.1. What is the effect of perceived difficulty on the shopping abandonment rate?

There were 21 participants who decided to abandon the shopping process (shopping abandonment rate = 13%). On average these participants reported significantly higher perceived decision difficulty than the ones who made a purchase from the webshop ($M_{Abandon}$=5.33, SD=1.683 vs. $M_{Purchase}$=4.28, SD=1.598, t(162)=2,802, p=,003). This indicates support for the hypothesis that higher perceived decision difficulty will increase the chance of shopping cart abandonment (H_9).

A binary logistic regression model was constructed to further study the extent by which perceived decision difficulty influences the abandonment rate. The results show that perceived decision difficulty was a significant predictor for shopping cart abandonment (Wald χ^2=10.335, *p*=.035).

The parameter estimates indicate that when consumers perceive the decision process to be difficult, the chance of abandoning the purchase is 22% (exp(-1.511)=0.221, p=.016). Moreover, when the process of making a decision was perceived as very difficult, the chance of abandoning the webshop was on average around 67% (exp(-0.405)=0.667, p=.422, ns). However, when consumers perceived the decision process as easy, the chance of abandoning the purchase online was only 9.4% (exp(-2.367)=.094, p=.020). Therefore, if the perceived decision difficulty chenges from difficult to easy, the chances of abandoning the shopping session decrease by around 43% (exp(-2,367)/(exp(-1.511)=0,43). The coefficients are presented in table 13.

Table 13

Results Summary for the Effect of Perceived Decision Difficulty on Shopping Abandonment

	Wald χ^2	β	Exp(β)
***Predictor Perceived Decision Difficulty** a)*			
Very easy	0.981	-1.204	0.300
Easy	8.867	-2.367*	0.094
Neither easy , nor Difficult	3.442	-2.159	0.115
Difficult	5.821	-1.511*	0.221
Very difficult (Intercept)	0.592	-0.405	0.667

Notes:
a) The predictor was corrected for quasi-complete separation. See appendix D3 for details
* Coefficient is significant at α=.05, p<.05

We also estimated that a webshop on which consumers perceive the decisional process as easy will have an abandonment rate of around 2.1% (exp(-2.367-1.511)=0.021) as compared to a webshop on which participants perceive the decision process as difficult (22%). We found therefore support for the statement that the higher the perceived decisional difficulty the higher the chance of abandonment of the purchase in online shopping.

The model goodness-of-fit was assessed with Akaike's information criterion coefficient (AIC=23.856). The values show a good model fit to complexity ratio, indicating that the model is parsimonius (i.e. includes the predictors that have a contribution in explaining the response variable).

In conclusion, we found that when consumers perceive the online shopping decision process as difficult they will likely abandon the webshop. The data showed also that decreasing the perceived decision difficulty had a significant impact on diminishing the likelyhood to abandon the webshop. For the e-commerce industry it is crucial thus to find ways of decreasing the decision difficulty perceived on their webshops.

5.4.2 How can the perceived decision difficulty be decreased?

In the previous section we found support to state that lowering the difficulty of the decision making process online is beneficial in reducing shopping abandonment . In this chapter we investigate the methods to lower the decision making difficulty.

To begin with, we have already found that consumers perceive the decision making process as difficult if they experience choice conflicts (see chapter 5.3.3). Hence we expect that reducing the choice conflicts would reduce the perceived difficulty.

One factor contributing to the reduction of choice conlflicts was identified when showing the alternatives with nonaligned attributes. It was found that it s*eemed to reduce* the number of choice conflicts by almost 21% as compared to the aligned attributes condition (β=-0.229, 1-exp(β)=0.205, p=.081, ns at α=.05 but significant at α=.10). Therefore we expected that when consumers compare alternatives with aligned attributes, they will perceive less decision difficulty than if the alternatives have nonaligned attributes (H_{1B}).

The data showed that manipulating the attribute alignment had a significant effect on the perceived difficulty but in a reversed way (F=4,322, p=.015). Nonaligned attributes were actually more appropriate for *reducing* the perceived difficulty than when alternatives had the attributes aligned on a single dimension (post-hoc analysis using Bonferroni corrected Confidence intervals, $_{95\%}$CI:(-1,64,-0,13), p=.015; see appendix E7). We found support for the *reversed* hypothesis, that when consumers compare alternatives with *nonaligned* attributes, they will perceive less decision difficulty than if the alternatives have aligned attributes on a single dimension (-H_{1B}). This result was surprising as it contradicted the expected situation in which it is easier to decide to choose, when alternatives are different on one dimension. A discussion about the possible explanations of such a situation is made in the discussion chapter (chapter 6).

Turning now to the information search effort as a possible way to reduce choice conflicts. We expected that the effort expended in searching for information is a potential influencer in increasing the perceived decision difficulty. Therefore we tested whether if more information search effort consumers expend will result in higher perceived decision difficulty (H_8).

The results show that the search effort influences the perceived difficulty significantly (Wald χ^2=7.004, p=.008). More specifically, an increase of the effort to search for information results in a greter chance of experiencing a very difficult shopping session (highly perceived difficulty) by 115% (β=0.143, exp(0.143)=1.154, p=.008), whereas the chance of experiencing the shopping process as difficult increases by 16 times when the consumer expends more search effort (β=2.794, exp(2.794)=16.339, p<.001, see table 14). For testing this relation between information search effort and perceived difficulty we fitted a multinomial logit linear model (goodness-of-fit criterion AIC=148.926).

Table 14

Results Summary for the Effect of Information Search Effort on Reducing the Perceived Decision Difficulty

	Wald χ^2	β	Exp(β)
Predictor Information search effort;			
Dependent variable: Perceived decision difficulty. Threshold = Very difficult [a)]			
Very easy	44.204	-2.907**	0.055
Easy	28.637	-1.393**	0.248
Somewhat easy	1.255	-0.245	0.783
Neither easy , nor Difficult	0.327	0.124	1.132
Somewhat difficult	30.875	1.356**	3.879
Difficult	67.631	2.794**	16.339
Information search effort	7.004	0.143*	1.154

Notes:
a) The Generalized linear model with ordinal response variable uses the highest level of the dependent variable compared to the threshold. The coefficients therefore are computed in reference to the threshold level.
* Coefficient is significant at α=.05, p<.05
** Coefficient is significant at α=.001, p<.001

The data show support for the predicted relation between information search effort and perceived decision difficulty. Therefore it is recommended that the information architecture of the webshops should be as simple as possible and provide sufficient usable tools to ease the search process. We argue that consumers will still get involved in searching for information but they will experience less effort in the process, thus leading to less perceived decisional difficulty.

To sum up, perceived decision difficulty is a crucial factor in determining consumers to abandon the shopping process. To lower the perceived difficulty, webshop owners and designers need to account for the way alternatives are presented on their websites and to make the information search process as easy as possible.

5.5. Maximization behavior

We expect that the goal to get the best will trigger a maximization behavior even though the consumer does not present a maximizing tendency.

5.5.1. What is the effect of maximization behavior on choice conflicts and perceived decision difficulty?

In the previous sections we have already investigated the relationship between priming for maximization behavior (task to buy the best possible photo camera) and the number of choice conflicts or the perceived decision difficulty.

We found that the participants primed for maximization behavior experienced on average around 16 choice conflicts (Exp(2.738)=15.460, p<.001), whereas those not primed experienced around 13 choice conflicts on average (with 20% less). However, not the same direct effect was observed on the perceived decision difficulty. There was no support for the conclusion that priming for maximization behavior is making the decisional process difficult. In other words, consumers instructed to buy the best posisible pohoto camera reported similar leveles of the perceived decision difficulty as the ones not instructed.

5.5.2. What is the effect of maximization behavior on the information search effort?

Maximization behavior had a significant effect on the effort to search for information. We tested whether consumers instructed to buy the best product expended more effort searching for information than the ones not instructed to buy the best product (H_6). For testing this hypothesis we fitted a Poisson model with the information search effort as the dependent variable. The model also included the individual tendency to search for alternatives (subscale of Maximization Inventory).

We found that priming for maximization behavior and the individual tendency to search for alternatives were both significant predictors for information search effort (Wald $\chi^2_{\text{MAX-Behavior-Task}}$=8, p=.005, Wald $\chi^2_{\text{Alternative-Search-Tendency}}$=13.795, p<.001, Wald $\chi^2_{\text{Interaction}}$=10.595, p=.001). We can conclude that shopping for the best product leads people into spending more effort to search for information. Moreover, the individual tendency to search for alternatives will also influence the information search effort. And because there is also a significant interaction effect, we argue that consumers primed for maximization behavior (i.e. to buy the best product) were expending more effort to search for information about the products. The effect is heightened by the individual tendency to search for alternatives. From the parameter estimates we saw that, on average, participants not primed for maximization behavior viewed around 3 pages per shopping session (exp(-0,826+1,653)=2,29). The model coefficients are illustrated in table 15.

Table 15

Results Summary for the Effect of Maximization Behavior on Information Search Effort

	Wald χ^2	β	Exp(β)
Predictors: Task Priming for Maximization Behavior;			
Individual Tendency to Search for Alternatives			
Primed for maximization behavior (Intercept)	4.365	-0.826*	0.438
Not primed for maximization behavior	8.000	1.653*	5.223
Tendency to search for alternatives	27.730	0.380**	1.462
Not primed for maximization * Tendency to search	10.595	-0.355*	0.701

Notes:
* Coefficient is significant at α=.05, p<.05
** Coefficient is significant at α=.001, p<.001

On one hand, priming participants for maximization behavior boosted the information search effort by 523% (Exp(1.653) = 523%, *p*=.005). This means that these participants visited on average around 13 pages per shopping session. Additionally, the individual tendency to search for alternatives amplified the search effort by around 146%. We argue that consumers shopping for the best product who are inclined to search for alternatives doubled their information search effort (exp (0.380) = 146%, *p*<.001).

On the other hand, consumers not primed for maximization behavior spent 40% less effort in searching for information than the others (exp(-0.826)=0.438, p=.037).. Similarly, the interaction effect was diminished by around 70% (exp(-0.355) = 0.701, *p*=.001). Thus, it can be concluded that consumers not shopping for the best product were spending less search effort when shopping online, even though they might have presented a higher individual tendency to search for alternatives. The model goodness of fit Akaike's criterion shows a satisfying fit to complexity ratio (AIC=693.511).

In conclusion, we found support for the statement that consumers adopting a maximization behavior were more likely to spend increased search effort when shopping online as compared to the others.

Separately, we also investigated whether comparing alternatives with nonaligned attributes will determine consumers to expend more effort in searching for information than if the alternatives have aligned attributes (H_{4B}). The data show no support for this relation. It seems that the attribute alignment did not influence significantly the information seach effort (Wald χ^2=3,082, *p*=.214, ns). The linear model goodness-of-fit to complexity ratio was moderate (AIC=723.525, see table 16).

To conclude, we argue that the interest to get the best product does not influence directly the perceived difficulty of the shopping process. Instead it influences significantly the number of choice conflicts and through the choice conflcits it plays a role in the decision difficulty.

Next, there were sufficient arguments to show that consumers wanting to buy the best product will spend considerably more effort than their counterparts, who are concerned to get any product that fits the needs and the budget.

We also found an interaction between the individual tendency to search for alternatives and the goal to get the best product. Consumers who were already inclined to search for alternatives spent twice as much information search effort in the online shopping environment.

5.6. Results summary

This chapter presents an overview of the results section, providing a summary view on the main findings of the experimanetal main study, focusing on the relationships between the constructs used in the research model. The syntetic view of the tested hypotheses and the statistical analsysis is presented in table 16. The parameter estimates and the model statistics are all avaialble in appendix E.

Table 16

Results Chapter Summary – Hypothesis Testing and Statistical Analysis

H_{1A}: Attribute alignment effect on choice conflicts Alternatives with nonaligned attributes will generate more choice conflicts than with aligned attributes			**Not Supported**
Quasi-Poisson Regression	Dependent: **choice conflicts (counts)**	Goodness-of-Fit AIC=1181.022	
Predictor: Attribute alignment		Wald χ^2 = 3.683	p = .081, ns

-H_{1B}: Attribute alignment effect on perceived decision difficulty Alternatives with aligned attributes will generate less decision difficulty than with nonaligned attributes			**Reverse [a)] Support**
One-way ANOVA			
Factor: Attribute alignment		F = 4.322	p = .015
H_2: Choice conflicts effect on shopping abandonment The higher the number of choice conflicts consumers experience online, the greater the chance of abandoning the shopping session			**Not Supported**
Binary Logistic Regression with logit link	Dependent: **conversion (binary)** [b)]	Goodness-of-Fit	AIC=78.793
Predictor: Choice conflicts		Wald χ^2 = 0.871	p = .351, ns
H_3: Choice conflicts effect on perceived decision difficulty The higher the number of choice conflicts consumers experience online, the higher decision difficulty consumers will perceive			**Supported**
Ordinal Logistic Regression	Dependent: **perceived decision difficulty (ordinal)**	Goodness-of-Fit	AIC=383.403
Predictor: Choice conflicts		Wald χ^2 = 8.437	p = .004
H_{4A}: Choice conflicts effect on the information search effort The higher the number of choice conflicts consumers will experience, the more effort they will expend in searching for information in an attempt to solve the choice conflicts			**Supported**
Ordinal Logistic Regression	Dependent: **information search effort (counts)**	Goodness-of-Fit	AIC=527.631
Predictor: Choice conflicts		Wald χ^2 = 298.821	p < .001
H_{4B}: Attribute alignment effect on the information search effort Alternatives with nonaligned attributes will determine consumers to expend more effort in searching for information than alternatives with aligned attributes			**Not Supported**
Poisson Regression	Dependent: **information search effort (counts)**	Goodness-of-Fit	AIC=723.525
Predictor: Attribute alignment		Wald χ^2 = 3.082	p = .214 ns
H_5: Maximization behavior effect on choice conflicts Consumers instructed to buy the best product will experience more choice conflicts than when not instructed to buy the best product			**Supported**
Quasi-Poisson Regression	Dependent: **choice conflicts (counts)**	Goodness-of-Fit	AIC=1179.385
Predictor: Task Scenario [c)]		Wald χ^2 = 4.228	p = .040
H_6: Maximization behavior effect on the information search effort Consumers instructed to buy the best product expend more effort searching for information than if they are not instructed to buy the best product			**Supported**

Poisson Regression	Dependent: **information search effort (counts)**	Goodness-of-Fit AIC=693.762	
Predictor: Task Scenario		Wald χ^2 = 8.000	p = .005
Covariate: Alternatives search tendency d)		Wald χ^2 = 13.795	p < .001
*Interaction effect Predictor * Covariate*		Wald χ^2 = 10.595	p = .001
H_7: Maximization behavior effect on perceived decision difficulty Consumers instructed to buy the best product will perceive more decision difficulty than when not instructed to buy the best product			**Not Supported**
One-sided T-test			
Factor: Task Scenario		t(162) = 0.609	p = .544 ns
H_8: Information search effort effect on perceived decision difficulty The more information search effort consumers expend the higher perceived decision difficulty			**Supported**
Multinomial Logit Regression	Dependent: **Perceived decision difficulty (ordinal)**	Goodness-of-Fit AIC=148.926	
Predictor: Information search effort		Wald χ^2 = 7.004	p = .008
H_9: Perceived decision difficulty effect on shopping abandonment Higher perceived decision difficulty will increase the chance of shopping cart abandonment			**Supported**
Binary Logistic Regression with logit link	Dependent: **conversion (binary)**	Goodness-of-Fit AIC=23.856	
Predictor: Perceived decision difficulty		Wald χ^2 = 10.335	p = .035

Notes:
a) Hypothesis H_{1B} was supported but reversed; nonaligned attributes perform better than aligned attributes in reducing the perceived decision difficulty;
b) The shopping outcome – conversion - was recorded in a binary variable with 1=purchase decision, 0=abandonment decision
c) Task scenario was used to instruct the participants for buying the best possible photo camera – it is a dummy variable, 11=not instructed, 21=instructed
d) Alternative search tendency measures the individual tendency to search for more alternatives while shopping – it is a subscale of Maximization Inventory scale

The relationships between the constructs used in the main experiment are presented in a schematic way together with the corresponding hypothesis in figure 10.

The model illustrates that choice conflict is a necessary but not sufficient condition for explaining the shopping cart abandonment in online shopping. Instead, choice conflict influences the perceived decision difficulty which then leads to shopping cart abandonment.

Information search effort and attribute alignment also influence the perceived decision difficulty; it was found to amplify the perceived decision difficulty. The chances of abandoning the shopping session increase when consumers expend more information search effort and the products are presented with attributes aligned on a single dimension.

The task to buy the best product increases both the choice conflicts and the information search effort. It seems that in this case consumers are prone to make extensive evaluations and

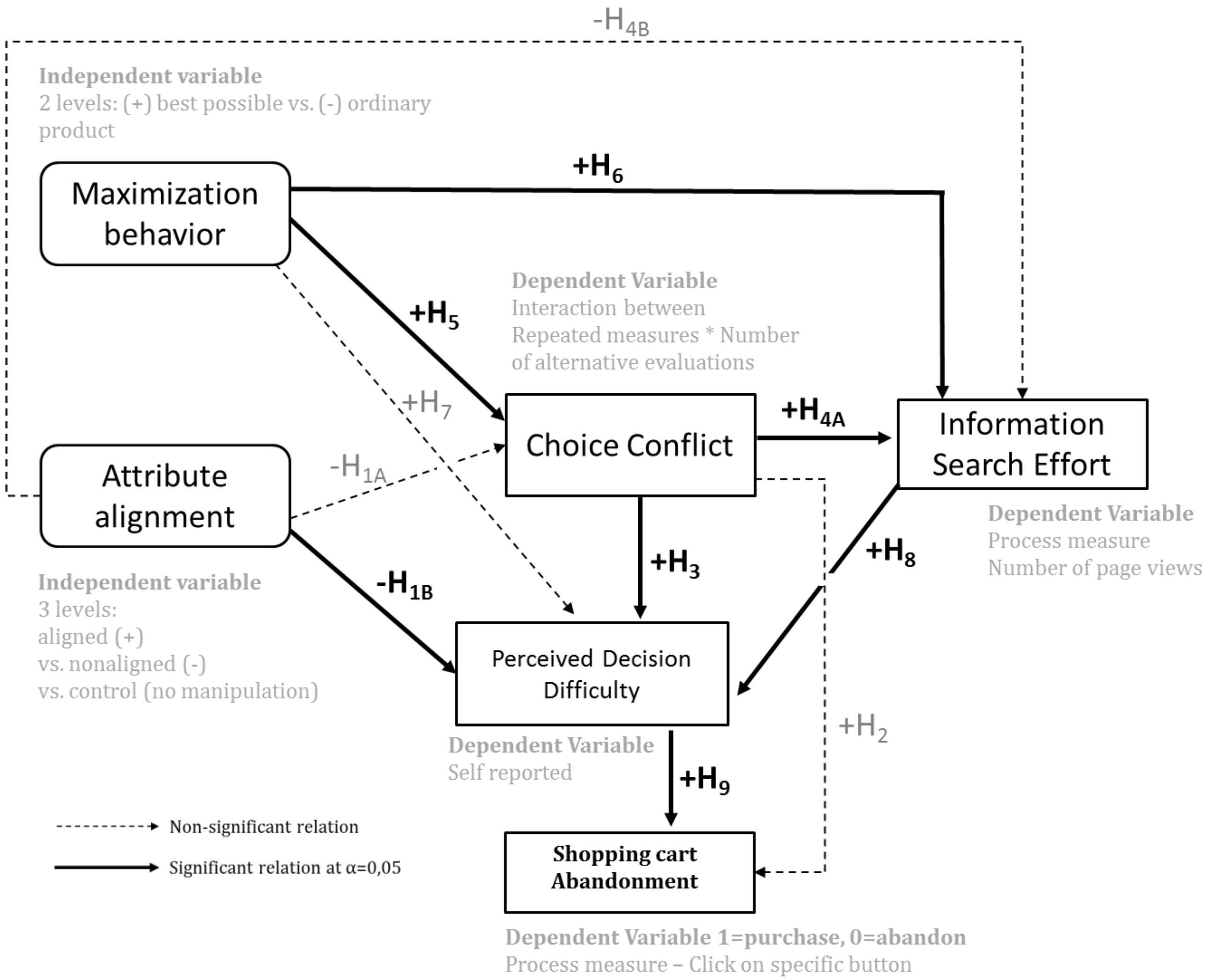

Figure 10 – Main experiment Research Model. Overview of hypothesized relations between the theoretical constructs. Dashed lines represent non-significant relations. Weighted lines represent significant relations at α=0.05; Hypotheses in dark-gray are not supported. Hypotheses in bold are supported.

comparisons between alternatives. This generates choice conflicts which will determine consumers to get involved in searching for information. In doing so the consumers experience increased decision difficulty which afterwards leads to shopping cart abandonment.

5.7. Other results

The experimental set up provided the means for collecting a vast amount of qualitative user data regarding the process of shopping online, such as mouse-tracking data, click-stream, attention heat-maps, user input, and the like. This information allowed us to get a peek on what the participant actually did while performing the shopping task. The data were collected unobtrusively; participants were informed that their mouse and browsing activity would be collected but there was no feedback (not even page loading delays) that something was in fact monitoring them. We argue therefore that, even though participants knew about the data collection, they were not aware when and how it happened.

Apart from these qualitative data we also collected, using repeated measurements, the decision difficulty during the shopping task. This was important for assessing the choice conflicts, as described in the methodology section. However, they were also inspected qualitatively to get a closer view of what was happening during the shopping session.

Therefore, we will report it briefly in this section using a combination of use-cases and other measures.

5.7.1. Decision difficulty reported during shopping

The repeated measurements of decision difficulty experienced during shopping were inspected for systematic differences between the participants primed for maximization behavior and the ones not so primed. Data indicates a pattern for experiencing difficulty during the shopping session on the experimental webshop. As such, a clear distinction was observable between the participants primed to buy the best

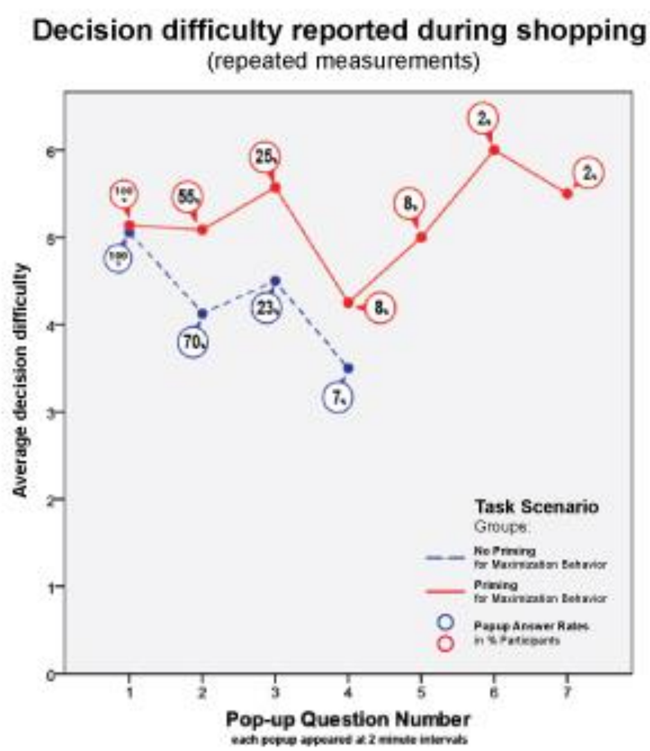

Figure 11 – Decision difficulty reported during the shopping process. The difficulty was averaged at each popup question for all participants per group. The percentages show the fraction of participants still shopping online at the moment of popup display. Each popup was displayed at fixed intervals of 2 minutes.

camera and the ones not primed for maximization behavior. The separation is visible in figure 11. First, it is evident that all of the participants not primed for maximization made a decision in the first 9 minutes (after popup 4 was shown), whereas around 20% of the participants primed for maximization behavior underwent longer decision making processes. The picture in figure 12 also shows an interesting pattern: between popup 3 and 4 (6 to 8 minutes after the beginning of the session) the difficulty reported by participants in both groups dropped in a similar way, but with different magnitudes.

The mouse-tracking data were useful in getting a glimpse of what really happened in this situation. We observed that participants used a new iteration of filtering the available alternatives based on budget. For instance, participant #105 narrowed the budget filter from the range of 0-300 to a 250-350 euros. We speculate that reducing the number of available products generated this decrease in difficulty as they had fewer products to choose from.

5.7.2 Decision difficulty reported after shopping

Participants also reported the perceived decision difficulty at the end of the shopping task. Although during shopping participants perceived on average a somewhat difficult decision process (*M*=4.97, *SD*=1.1269), after the session they reported **less** decision difficulty (*M*=4.41, *SD*=1.6426, towards the middle point); the difference was significant (*t(163)*=3.478, *p*=.001). There is a mismatch between the decision difficulty participants reported at the end of the shopping process and the decision difficulty reported during the session. Figure 12 illustrates the different perceived decision difficulties.

The participants were more likely to report less difficulty if they experienced either a more pleasant end

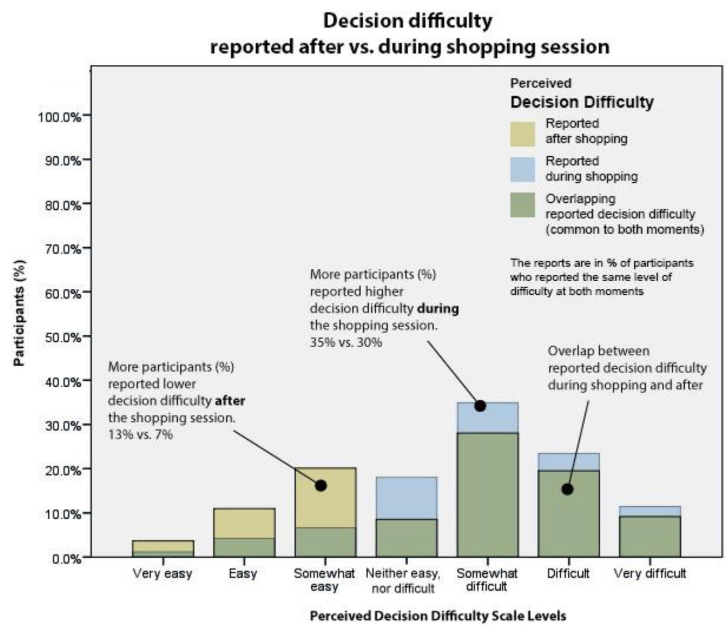

Figure 12 – Decision difficulty reported during and after shopping. The reports are in % of participants and illustrates the overlapping and the differences between the decision difficulties experienced during and after the shopping session.
Note: the chart contains two standardized bar-charts which were juxtaposed using AND blending mode to illustrate the similarities and differences between the two charts.

of task (e.g. finding what they had looked for) or a less difficult “peak” moment. As a result, the perceived decision difficulty reported during the shopping session explains around 32% of the perceived difficulty reported after the session (r=.563, R^2=.317, p<.001).

We believe this resembles the Peak-End rule introduced by Fredrickson and Kahneman (1993). Namely, it suggests that a difficult decision making process could be reversed if consumers have had the impression of a good deal (even if they struggled to get it). Although we did not investigate this particular situation in our study, we did collect data about the satisfaction with the decision made. The correlation analysis seems to support the existance of a peak-end effect, as higher satisfaction with the decision made was associated with less overall difficulty reported after the shopping session (r=-.474, p<.001), while there appears to be no connection with the averaged choice difficulties reported via popups (r=.005, p=.939, ns.).

In conclusion it is possible that this occurrence of a peak-end effect in the online decision making process could indicate a method to increase consumer satisfaction with the webshop. We think following this research path in identifying possible factors to reverse the perceived decision difficulty during shopping online could be fruitful.

6. Discussion

The goal of the present research project was to study online shopping abandonment from a decision making perspective and identify to what extent choice conflicts experienced by consumers influence their decision to abandon the shopping cart.

The main findings indicate that choice conflicts are influencing the decision to abandon the shopping in the online environment, but not in a direct way. Instead, choice conflicts contribute significantly to the perceived decision difficulty, which in the end influence abandonment of the shopping cart.

The results show that if consumers perceive the decision process as difficult, the chance of abandoning the shopping session is around 22%, i.e. 43% higher than when consumers perceive the decision process as easy.

Choice conflicts were an important predictor of perceived difficulty, although not the only one. The research shows that, apart from choice conflicts, the information search effort is also a key factor in creating decision difficulty. Moreover, we can see in figure 11 that choice conflict has a double influence on perceived decision difficulty: first as a direct predictor, and second as a moderator through information search effort. We found that consumers experiencing choice conflicts try to search for information in order to get support for resolving the choice conflict. In doing so they run the risk of getting too much information, especially online. The effort of processing the information adds up to the overall perceived decision difficulty, resulting in a higher chance of abandoning the webshop.

The results of the main experiment indicate some possible ways to lower the difficulty to decide when shopping online.

For instance, we observed that displaying products with nonaligned attributes decreased the decision difficulty perceived by our participants, contrary to what we expected. It seems that participants were more likely to perceive less difficulty when the alternatives available were displayed in a heterogeneous rather than homogeneous way. Namely, when products were identical on most attributes and the only difference was the variation of one attribute, consumers had to compare very similar alternatives and thus it was harder for them to find a clear dominant product. Surprisingly, displaying the alternatives with nonaligned attributes seemed to make it easier to choose between products. A potential explanation for this is the possibility to find a dominant product faster and easier, because varying the levels of all attributes could make one product better in all attributes at once (through random allocation), dominating the others.

This suggests an interesting method for improving the way webshops display their products. We observed that when participants filter the products based on some attributes then the resulting products are displayed in a homogenous way, trying to respect the filter. However, showing products like this makes them all very similar with respect to the filtered attributes. Moreover, we found that consumers perceive higher levels of decision difficulty when they need to choose between products that are very similar, so maybe a better solution would be to display the products emphasizing the differences between them rather than the similarities. We intend to elaborate on this in the future with a new experiment.

To sum up, webshop owners and designers are advised to arrange the products displayed on the page in such way as on each results page there should be one dominant alternative. Moreover, it seems that consumers search information on products in order to find support for their decisions. As such, it is recommended that each product page should present information designed to address this “decision support” problem to satisfy the need for searching information. Also we recommend that the system should acknowledge if a consumer visits more than 12 products in a single session, as this is an indicator of increased information search effort and higher decision difficulty. In such situations the webshop should include in the results products that dominate the ones considered by the consumer, in order to make it easier for the consumer to decide, lowering the chance for abandonment.

Consumers are advised to switch to a simplicity seeking shopping strategy if their goal when starting the online shopping session was to find and purchase the best product. This will enable them to experience a less difficult shopping process and will also facilitate a better decision making process. Consequently they will likely experience less frustration and more satisfaction when shopping online.

6.1. Theoretical implications

An important contribution is that in this study we mapped a particularity of the choice conflict manifested in the online environment. Namely, we identified two distict moments of choice conflicts: superficial conflict, which occurs when consumers scan all the products available in order to decide which one to choose, and analytical choice conflict which happens when consumers make value evaluations based on the details of the considered alternatives. The superficial choice conflict is specific to environments in which the available alternatives are displayed in blocks or lists on screen and consumers need to decide which alternative to select for detailed inspection.

We also found that in the online shopping contexts choice conflicts influence the decision to defer choice indirectly. In other words, choice conflicts increase the perceived decision difficulty which afterwards determines the consumers to abandon the online shoppingsession. This is diffferent from the results of Tversky and Shafir (1992) for offline shopping, in which choice conflicts where directly influencing the decision to defer choice. Probably this difference stems from the fact that in the online envrionment consumers have easier access to all sorts of information about products (reviews, word-of-mouth, comparisons, best buy advices, and the like) and thus they can try to solve the choice conflicts much easier.

Another important contribution stems from the findings which support the multidimensionality of the maximizing tendency as an individual trait. Unlike Schwartz et al. (2002), we found that people can manifest the behavior of a maximizer even though their individual tendency is more of a satisficer (i.e. lower scores on the Maximization Tendency Scale). Moreover, it seems that the indiviual tendency for maximizing is not necessarily influencing the decision making process. Instead we observed that shopping for the best product is more likely to trigger a maximization behavior, regardless of the individual's tendency for maximizing. In this respect we concur with the conclusions of Rim et al. (2011) and suggest that the dimensionality of the maximizing tendency construct should be reconsidered.

We also found a surprising implication from the way the attribute alignment influenced the perceived decision difficulty. It seems that displaying the products with nonaligned attributes significantly decreases the perceived decision difficulty, making it easier for consumers to choose when shopping online. This was counterintuitive as we expected that if all the prodcuts are similar in all but one dimension it would be easier for consumers to construct a dominant variant and thus make a choice. However, our results indicate that, at least in online contexts, it would be easier to make a decision out of a more heterogeneus set of available alternatives than from a homogeneous one. We believe that more research is needed on this line of reasoning regarding the way products are displayed on the webshops result pages.

One of the most important contributions is the finding that choice conflicts together with perceived difficulty are playing an influential role on the shopping cart abandonment rate for the online shopping industry. The theoretical implications of this finding are twofold.

First, it extends the knowledge of the problem of online shopping abandonment by adding empirical evidence for an alternative explanation of the high abandonment rates recorded in the e-commerce industry.

Second, it suggests that there are more factors that can influence the decision difficulty perceived while shopping online, apart from the ones already considered by the industry and presented in the preamble of this research. To stress the importance of this, consider for instance the finding showing that the chance of abandoning the webshop was around 22%. when consumers perceived the decision process as difficult. In other words, perceived decision difficulty explains roughly 22% of the online shopping abandonment rate.

Finally, the study approached decision making in the online context using a set of mixed experimental research tools which intersects technological advances with rigorous experimental designs. This allowed the execution of a controlled experiment at a larger scale, mediated by the internet environment, outside the lab. Although still in the process of improvement, we think that the main study design reveals a path towards achieving higher control in experiments conducted at big-data scale, in a cost effective way.

6.2. Practical implications

We believe that our findings will help online business owners and marketing managers to gain a new viewpoint on the reasons leading to shopping cart abandonment rates. More specifically, the results indicate an important cause of the shopping cart abandonment, rarely approached until now. This points towards the need for improving the webshops in order to leverage the difficulty of the shopping process. To achieve the goal of lowering the decision difficulty, our findings suggest focusing also on the way the products are served and displayed in the result webpages. It seems that displaying products in a more heterogeneous way on the results pages of the webshops helps reduce the perceived decision difficulty. It seems that making it easy for consumers to reach a decision while shopping online will reduce the shopping abandonment rate.

The benefits of implementing these findings would be twofold: first consumers will experience less difficulty and frustration while shopping online, and second, online businesses will see improvements on their online conversion rates and return on investments.

In summary, we hope that studies such as this will provide arguments to invest and research in domains such as adaptive technologies for developing consumer models and webshops that react to consumer’s behavioral patterns. We think that this will lead to a better online shopping environment for both the consumers and the e-commerce industry.

6.3. Limitations

The present research presents several limitations generated mainly by the constraints imposed by running the experiment online. Among these, we consider limited possibilities of control during the shopping experiment as one of the most important limitations. Although the experimental material was well controlled by the experimental setup and design, little control could be exerted on the whole online setting in which people participated. For instance, one of the requirements was for the whole participation to be done in one setting. However, there were no possibilities to control it, apart from asking the participants explicitly in the instructions. This limitation would have been better addressed in a laboratory experiment.

Another limitation of the study was that, due to the internet architecture, the experiment was restricted to only one website, therefore creating a somewhat artificial environment for shopping online. The shopping task scenario was used to address this particular issue, but even so we are aware that there is no way to ensure total ecological validity while conducting such experiments, simply because the obtrusive character of research itself. We think that these limitations are inherently tied to the online environment and, at least so far, there have been limited possibilities to remove them completely.

Turning to the decision outcomes, the experimental design allowed for capturing the participants' behavior of in regard to the decision to purchase or to abandon. The participants could decide to purchase the product by pressing the buy button, or to abandon the purchase by pressing “I decide not to buy” button. While the first action has intrinsic ecological validity for assessing the buying intention, the second one raises some discussion about its limited ecological validity. As such, it can be argued that in a real online shopping situation consumers do not need to take a specific action – on the webshop – for abandonment. Instead, they can simply close the browser or switch to another website. Nonetheless, we think that consumers are still performing an action of “not choosing”, even though it is not explicit. Therefore we argue that using a button to signal abandonment improved the “reality” of the research situation. It seems that otherwise, in order to achieve closure of their participation they would buy a product even though their intention would have been to abandon (Dhar & Nowlis, 2004; Odekerken-Schröder & Wetzels, 2003).

A separate class of limitations comes from the sample used. Namely, the sample size, composition, and the sampling method do not guarantee representativeness. Nevertheless, by random assignment, we ensured that the experimental groups were comparable in respect to the variables measured. Hence, we have no particular reasons to doubt the internal validity of the research; the constructs were operationalized and we used reliable measurement instruments for all the quantitative data. Regarding the measurement instruments, we identified at a later stage a potential limitation of the instrument used to measure the superficial choice conflicts during the shopping session. Namely, the item presented in the popups contained the "neutral" as the middle point of the 7-points scale instead of either labelling it "neither easy, nor difficult" or simply just labelling the extremes and leaving the others un-labelled. Although this can raise concerns regarding the consistency of the scores obtained from this item we argue that it did not influence the overall results, mainly because the data show no systematic deviations toward the middle-point,which suggests that this did not influence the response style. Moreover, it seems that for 7-points Likert scales the effect of labelling the midpoint is not affecting the response style (Weijters, Cabooter, & Schillewaert, 2010), especially when the question asked is important, sensible or complex (Edwards & Smith, 2011; Wakita, Ueshima, & Noguchi, 2012).

To wrap up, we believe that the main conclusions of this research can be considered valid starting points for future investigations and replication on the field of online decision making.

6.4. Future research

During the present research project we observed new directions of research regarding the decision making process in the online shopping environment.

We noticed that using comparison websites instead of starting directly with a webshop meant less choice conflict and decision difficulty for the participants. We think that the acceptance, adoption and use of such online tools represent an interesting path for future research, as it offers promising findings in reducing online decision difficulty.

Next, it seems that displaying the available alternatives in a more heterogeneous way will lower the perceived decision difficulty. We found this to be a surprising result, contradicting our expectations. We recommend future research on this topic of attribute alignment as we observed that displaying products with nonaligned attributes performed better in reducing the perceived decision difficulty than any other way.

Another interesting research direction suggested by our findings is the multidimensional character of the maximizing tendency construct and the inconsistencies between manifesting a maximization behavior and having a lower tendency to maximize the output.

In general, we hope that our findings will encourage future research on the decision making process manifested in the online shopping context, in order to extend the knowledge in this increasingly important domain.

Appendix

Appendix A – Exploratory study materials

Table A-A1 – Exploratory study questionnaire 1 – Before starting the shopping session

#	Item	Scale	Observations
Maximizing Tendency Scale [a)]			
1.	No matter what it takes, I always try to choose the best thing.	Strongly disagree – Strongly agree	1-5 points
2.	I don't like having to settle for "good enough"	Strongly disagree – Strongly agree	1-5 points
3.	No matter what I do, I have the highest standards for myself.	Strongly disagree – Strongly agree	1-5 points
4.	I am a maximizer.	Strongly disagree – Strongly agree	1-5 points
5.	I will wait for the best option, no matter how long it takes.	Strongly disagree – Strongly agree	1-5 points
6.	I never settle for second best.	Strongly disagree – Strongly agree	1-5 points
7.	I am uncomfortable making decisions before I know all of my options.	Strongly disagree – Strongly agree	1-5 points
8.	Whenever I'm faced with a choice, I try to imagine what all the other possibilities are, even ones that aren't present at the moment	Strongly disagree – Strongly agree	1-5 points
9.	I never settle.	Strongly disagree – Strongly agree	1-5 points
10.	In the last three months, how often did you search for information about Computers/Mobile phones/Photo cameras/Household electronics/Computer accessories? [b)]	Never / Once / Several times	
11.	I have a preference for one or more brands in this product class Computers/Mobile phones/Photo cameras/Household electronics/Computer accessories [b)]	Strongly disagree – Strongly agree	1-5 points
12.	I am not at all familiar with these products:	Laptops / Digital cameras / External Hard drives / Printers / TVs Mobile phones	(select all that apply)

Notes:
a) MTS based on Dhar et al (2008).
b) The question was repeated for each product category

Task Scenario: You need to buy [*product*] and decided to do it online. Using any web shop you prefer try to buy the product online, exactly as you would do it from your home. You have [*budget*] Euros available to spend but you can decide to spend more or less if you think it's worthy. Also, as in a real shopping situation, you can decide not to buy if you don't find a good option. The study ends when you get to the payment page or you decide to abandon the shop. During the study please do not forget to think out loud.

Table A-A2 – Products and available budget

Product Name	Budget (EUR)
TV	220
Digital Photo Camera	140
Laptop	550
Mobile Phone	150
Inkjet Printer	70
External Hard-drive	110

Table A-A3 – Exploratory study questionnaire 2 – After the shopping session

#	Item	Scale	Observations
Perceived Decision Difficult, Satisfaction			
1.	How difficult was it to make a decision involving a choice between the alternatives available?	Very difficult – Very easy	1-5 points, recoded
2.	How satisfied you are with the decision made?	Very unsatisfied - Very satisfied	1-5 points
3.	How often do you shop online?	Less than 1 time per month / 1 – 2 times per month / 3-5 times per month / More than 5 times per month	
4.	Demographics (age, nationality, gender, education)	Self-reported	

Appendix B – Exploratory study data analysis materials

Table A-B1 – Exploratory study Coding Scheme

ID	Code	Description
Task related		
1.	SHS	Shop selected – participant access a web-shop for performing the task
Decision strategy		
2.	RF	Ratings filter – participant filter the alternatives based on reviews and ratings
3.	EBA	Elimination by aspect decision strategy – participant narrow the alternatives by hiding any alternative that does not fit into a particular criteria
Alternative-Attribute Evaluation		
4.	D-	Decision hinder – an event that hinders the participant decision
5.	D+	Decision favorize – event that help into making a decision
6.	D--	Decide not to buy – abandon the shopping session without buying
7.	AE	Alternative evaluation – participant is parsing through a whole list of alternatives (i.e. resulting of a EBA filter)
8.	ASL	Alternative selected – participant selects one alternative for evaluation
9.	ATE	Attribute evaluation – participant evaluates the attributes of the selected alternative
Attribute alignability - tradeoffs		
10.	AT	Attribute tradeoff – participant make attribute (features) tradeoffs between the selected alternatives
11.	ATA+; ATA-	Attribute alignability – (+) the alternatives are aligned, allowing inter-alternative comparisons on a single dimension; (-) the attributes are not aligned, favorizing tradeoffs between alternatives (alternative A is better on X attribute but worse on Y attribute)
Choice conflict		
12.	ATC	Attribute tradeoff conflict – participant is experiencing difficulty in choosing because of attribute tradeoffs
Information Search		
13.	IOV	Information overload – participant is exposed to a lot of alternatives
14.	IWS	Inter Webshop Comparisons – participant choose a product but then decides to search for that product in different webshops for trying to get a better deal (cheaper price, accessories, faster delivery and the like)

Appendix C – Experimental main study materials

Task scenario

You find that your old [*very good*] photo-camera is damaged and decide to shop online for a new [*good*] digital photo-camera to replace the broken one. You searched for possible web shops and found the AShop-X website which looks like having what you need.

Your plan is to buy [*a new/best possible*] photo-camera in under 300 Euro, but if you find a better variant you can go up to 340 Euro. As in real life, you can decide also not to buy anything if you cannot find a photo-camera that fits your preferences.

When you'll press next you will be taken to the A-Shop X Website.
If you need to see the above task again you will have this possibility on the website.

Instructions (on webshop)

Use the current website to shop and please do not navigate away until the experiment is finished. From time to time a popup will appear asking you one question and you will need to answer it to continue.
If you found something suitable and decide to buy it click on the "**Buy this product**" button. If you decide that you do not want to buy anything then click on the "**I decided not to buy**" button. After that you will be redirected to a short survey.
Thank you for you cooperation and participation!

Questionnaire

Table A-C1 – Experimental main study questionnaire 1 – Before starting the online shopping experiment

#	Item	Scale	Observations
Demographics and eligibility criterion, Task scenario			
1.	Demographics (gender, age, education)	Self-reported	
2.	Did you make at least one online purchase In the last six months?	Yes/No	If no is selected then end experiment
3.	How often do you shop online?	Less than Once a Month Once a Month 2-3 Times a Month 4-5 Times a Month More than 5 Times a Month	
4.	In the last three months, how often did you search online for information about Digital Photo Cameras?	Never – Very often	5 points, Semantic differential
5.	I have a preference for one or more brands in this product class - Digital Photo Cameras	Strongly disagree – Strongly agree	5 points, Likert scale
6.	Task scenario	[primed/not primed] for buying the best product	Randomized by Qualtrics

Table A-C2 – Experimental main study questionnaire 2 – After the online shopping experiment

#	Item	Scale	Observations
Various items			
1.	How difficult was it for you to make a decision?	Very Difficult – Very Easy	7 points scale, recoded
2.	How satisfied are you with the decision made?	Very unsatisfied – Very satisfied	7 points scale
3.	How likely it is that you will search the product that you choose on other webshops, before actually buying it?	Very Unlikely, Very Likely	7 points scale, the question appear only if participant decided to buy
4.	If you were to shop for a photo camera for real, how many photo cameras would you consider before choosing?	Self-reported	
5.	How many alternatives did you consider during the shopping session?	Self-reported	
6.	I am confident about my ability to buy a photo-camera online	Strongly disagree – Strongly agree	7 points scale
Involvement with Product Class (CIP scale)			
7.	Photo cameras are very important to me	Strongly disagree – Strongly agree	7 points scale
8.	Photo cameras are an important part of my life	Strongly disagree – Strongly agree	7 points scale
9.	For me photo cameras do not matter	Strongly disagree – Strongly agree	7 points scale, recoded
Maximization Inventory Scale – Satisficing subscale; 7 points scales, Strongly disagree – Strongly agree			
10.	I usually try to find a couple of good options and then choose between them		
11.	At some point you need to make a decision about things.		
12.	In life I try to make the most of whatever path I take		
13.	There are usually several good options in a decision situation		
14.	I try to gain plenty of information before I make a decision, but then I go ahead and make it		
15.	Good things can happen even when things don't go right at first		
16.	I can't possibly know everything before making a decision		
17.	All decisions have pros and cons		
18.	I accept that life often has uncertainty.		
Maximization Inventory Scale – Decision Difficulty subscale; 7 points scales, Strongly disagree – Strongly agree			
19.	I usually have a hard time making even simple decisions		
20.	I am usually worried about making a wrong decision.		

21. I often wonder why decisions can't be more easy

22. I often put off making a difficult decision until a deadline

23. I often experience buyer's remorse

24. I often think about changing my mind after I have already made my decision

25. The hardest part of making a decision is knowing I will have to leave the item I didn't choose behind.

26. I often change my mind several times before making a decision

27. It's hard for me to choose between two good alternatives

28. Sometimes I procrastinate in deciding even if I have a good idea of what decision I will make

29. I find myself often faced with difficult decisions

30. I do not agonize over decisions.

Maximization Inventory Scale – Alternative Search subscale; 7 points scales, Strongly disagree – Strongly agree

31. I can't come to a decision unless I have carefully considered all of my options

32. I will continue shopping for an item until it reaches all of my criteria

33. I usually continue to search for an item until it reaches my expectations

34. When shopping, I plan on spending a lot of time looking for something

35. When shopping, if I can't find exactly what I'm looking for, I will continue to search for it

36. I find myself going to many different online stores before finding the thing I want

37. When shopping for something, I don't mind spending several hours looking for it

38. I take the time to consider all alternatives before making a decision

39. When I see something that I want, I always try to find the best deal before purchasing it

40. If a store doesn't have exactly what I'm shopping for, then I will go somewhere else

41. I just won't make a decision until I am comfortable with the process

Appendix D – Experimental main study – Statistical procedures checks

D1. Choice conflicts

The dependent variable contains count data (number of choice conflicts). Hence, the variable range belongs to [0,+∞) interval and thus a normal distribution of the response variable could not be assumed (also visible in figure A-D1-1)

The distribution histogram of the dependent variable shows the violation of normality on the response variable (fig. A-D1-1). Subsequently, the homoscedasticity between the experimental groups was inspected graphically. The chart A-D1-2 illustrate that equal variances assumption is also broken; the data show outliers and differences in the spread and range in both groups. The maximizing group present an extreme outlier (participant #129) who inspected 22 products and reported a weighted average difficulty of 4 (88 estimated conflicts). The mouse data for this participant revealed a shopping session of around 15 minutes with a navigation path length of 67 pages. Overall, no suspicious behavior was observed for this participant, each of the 22 products being inspected in a consistent pattern (i.e. mouse moving on the product features of interest, mouse moving from top left to the center, scrolling, image inspection). Therefore, there is no reason to believe that the data collected are not suitable for the analysis. It seems that respondent #129 was really involved with the task of finding the best possible digital camera.

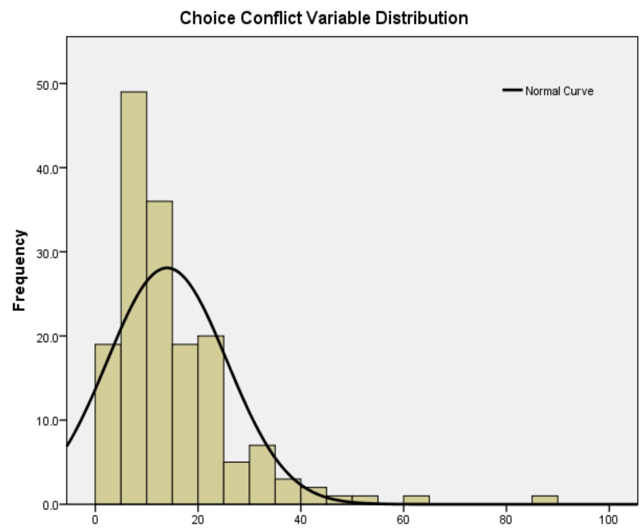

Figure A-D1-1 – distribution of the dependent variable – choice conflicts. The variable contains count data, range [0,+∞)

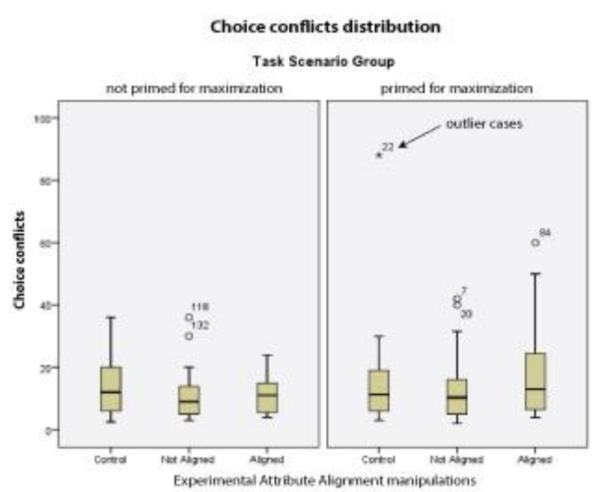

Figure A-D1-2 – Homoscedasticity visual test (equal variances)

The violation of the assumptions shows that the model do not follow a normal linear method.

Therefore, the best method for analyzing further is to use Generalized Linear Model analysis. As the respondent variable consists of counts, the appropriate method is to use a Poisson distribution with the log link function to cover the whole interval from (-∞,+-∞). According to Zuur, Ieno, and Elphick (2010), when dealing with count data, overdispersion needs to be assessed as it could raise problems of robustness of statistical analysis. Overdispersion phenomenon happens when the variance of the dependent variable is larger than its mean. Usually outliers in the count data are first signs of overdispersion. In the data the variance is considerably larger than the mean (*M*=13.98, *Var*=135.613) so we can conclude that the response variable is highly overdispersed. Dealing with such data requires a quasi-poisson model, and thus the appropriate analysis is a Generalized Linear Model with a tweedie log link (Dean, 1992; Kokonendji, Demétrio, & Dossou-Gbété, 2003; Moshitch & Nelken, 2014).

D2. Information search

The objective measurement of the search effort will be used further as the dependent variable in the model. Because the dependent variable contains count data it cannot be assumed to follow a normal distribution (see figure A-D2-1). Moreover, the response variable present moderate data overdispersion (Var = 6.706 > M=2.93) due to outliers. When performing hypothesis testing with overdispersed count data a conservative approach is recommended. Because the data are not zero-inflated (min = 2) a negative binomial model is not appropriate. Instead, it is advised to use the Pearsson Chi2 scaled confidence intervals to inflate the standard errors of the parameter estimates (Cameron & Trivedi, 2013). Therefore, for testing the second hypothesis, whether maximizing has an effect on increasing the information search effort as compared to the satisficing group several Poisson GzLM regression models were constructed.

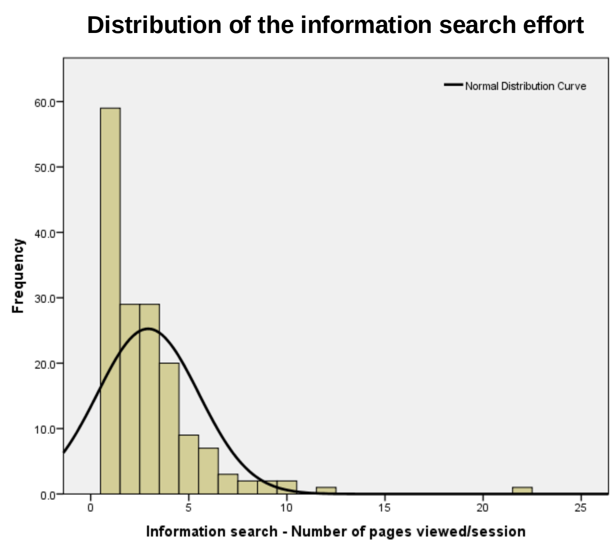

Figure A-D2-1 – Distribution of the information search effort (page views / session)

D3. Perceived decision difficulty – recoding dependent variable

Because shopping variable was binary (1/0) and the perceived decision difficulty was ordinal (1-7 semantic differential), the relation was tested using a χ^2 association test. It turns that there is a significant association between the two variables (χ^2=15.178, p=.019). This means that shopping abandonment varies systematically with the changes in the perceived difficulty (figure A-D3-1). From the chart it is also visible that the participants who converted (bought) are relatively equally distributed across the levels of the independent variable (perceived difficulty), while the other group is not present in all the levels of the predictor.

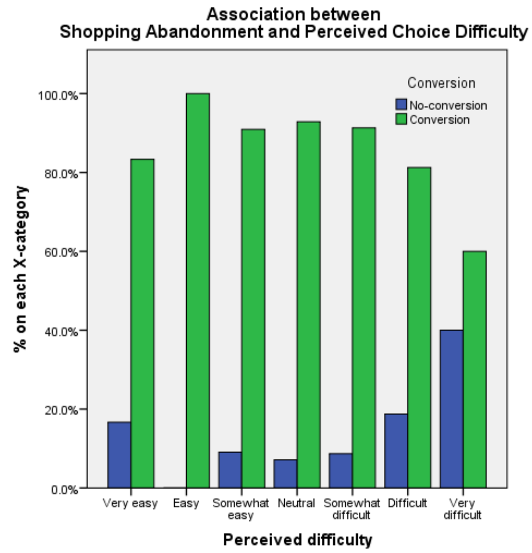

Figure A-D3-1 – Distribution of perceived decision difficulty within the shopping abandonment variable. In the chart the association between variables is visible.

This raise the problem of quasi-complete separation in the binary logistic regression method. This means that the dependent variable separates the predictor levels and there are missing categories across levels; therefore the maximum likelihood function cannot be estimated. Although the model fit is not affected by this problem, drawing inference from the model is not recommended. However, a method to correct for this situation is to re-categorize the predictor variables into fewer categories, if this operation make sense and the outcome variable is present across all levels (Altman, Gill, & McDonald, 2004). Generally ordinal variables can be reorganized into fewer categories. In this particular case since the variable of interest is the perceived difficulty, reported on a 7 points semantic differential scale, ranging

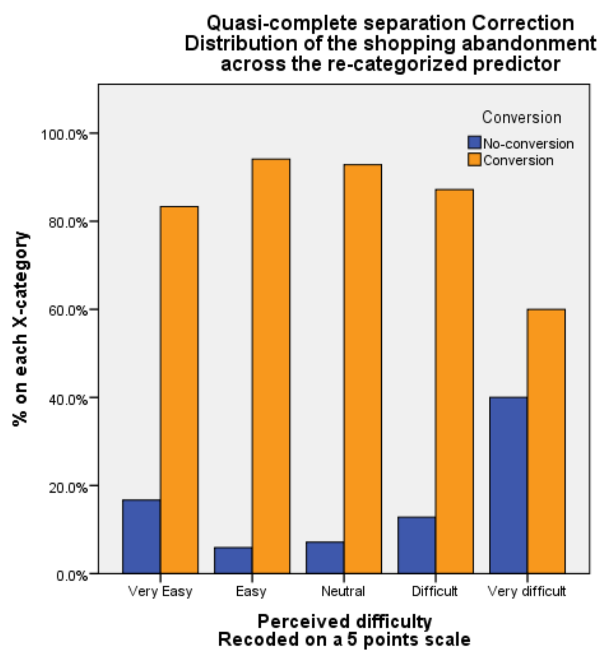

Figure A-D3-2 – The corrected variable for quasi-complete separation. The shopping abandonment variable was corrected by transforming the code form 7 to 5 levels.

from very easy to very difficult, we argue that it makes sense to transform this variable into a 5-points semantic differential.

The re-coding scheme was as follows:

- the extremes (1 and 7) remained extreme points, but the 7 was recoded into 5;
- the mid point (4) remained mid-point and was recoded to 3;
- the levels 2 and 3 (easy and somewhat easy) were grouped together and recoded as 2 - easy;
- the levels 5 and 6 (somewhat difficult and difficult) were grouped and recoded as 4 – difficult.

The chart illustrates the recoding operation and we can observe that the outcome variable is present across each levels of the predictor. Additionally, the recoding operation did not alter the overall distribution of the data (figure A-D3-2).

D4. Control for potential confounding variables

Table A-D-1. Main Study experimental design; Control for confounding variables

Confounding Variable	Abandonment rate Contribution a)	Procedure
unexpected costs (shipping or taxes) in the final step	56%	constant, no unexpected costs (what you see is what you pay)
just browsing behavior	37%	controlled via purchase task
better price elsewhere	36%	only main session is permitted
price too expensive	32%	controlled price range within scenario budget
Currency	13%	constant, Euros
Delivery options	16%	free next working day delivery
Website technical problems b)	40%	experimental website

a) According to WorldPay report (2012) in Statista (2015),
b) Compound variable covering all the technical aspects of the website excluding payment errors. See WorldPay report (2012). The website was designed, implemented and coded by the researcher.

Appendix E – Experimental main study – Statistical hypothesis tests

E1. Test Hypothesis H_{1A} – Chapter 5.3.1.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	2499.602	1	.000
Attribute Alignment	3.683	2	.159
Akaike's Information Criterion (AIC)	1181.770		

Dependent Variable: choice conflicts

Model: (Intercept), Attribute Alignment

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test			Exp(B)
			Lower	Upper	Wald Chi-Square	df	Sig.	
(Intercept)	2.715	.0906	2.537	2.892	898.680	1	.000	15.102
Control	-.021	.1261	-.268	.226	.028	1	.867	.979
Nonaligned	-.229	.1312	-.486	.028	3.040	1	.081	.795
Aligned	0[a]	.	.	.	.	.	.	1

Dependent Variable: choice conflicts

Model: (Intercept), Attribute Alignment

a) Set to zero because this parameter is the reference

E2. Test of hypothesis H_5 – Chapter 5.3.1.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	2502.498	1	.000
Task Scenario	4.228	1	.040
Akaike's Information Criterion (AIC)	1179.235		

Dependent Variable: choice conflicts

Model: (Intercept),

Task Scenario (priming/no priming for maximization)

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test			Exp(B)	95% Wald Confidence Interval for Exp(B)	
			Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
(Intercept)	2.738	.0719	2.597	2.879	1452.301	1	.000	15.460	13.429	17.798
Not primed	-.216	.1052	-.422	-.010	4.228	1	.040	.806	.656	.990
Primed for maximization	0[a]	.	.	.	.	.	.	1	.	.

Dependent Variable: Choice conflicts

Model: (Intercept), Task Scenario (priming/no priming for maximization)

a. Set to zero because this parameter is the reference.

E3. Hypothesis H_2 test – Chapter 5.3.2.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	17.016	1	.000
Choice conflicts	.871	1	.351
Akaike's Information Criterion (AIC)	78.793		

Dependent Variable: Shopping (1=Buy/0=Abandon)

Model: (Intercept), Choice conflicts

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test			Exp(B)	95% Wald Confidence Interval for Exp(B)	
			Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
(Intercept)	-1.606	.3892	-2.369	-.843	17.016	1	.000	.201	.094	.431
Choice conflicts	-.024	.0260	-.075	.027	.871	1	.351	.976	.928	1.027

Dependent Variable: Shopping (1=Buy/0=Abandon)

Model: (Intercept), Choice conflicts

E4. Hypothesis H_2 test – Chapter 5.3.3.

Correlation

		Perceived Decision Difficulty
Choice conflicts		.218**
	p-value	.005

**Significant at .01 level

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
Choice conflicts	8.437	1	.004
Akaike's Information Criterion (AIC)			383.403

Dependent Variable: Perceived Decision Difficulty

Model: (Threshold), Choice conflicts

Parameter Estimates

Parameter		B	Std. Error	95% Wald Confidence Interval		Hypothesis Test			Exp(B)	95% Wald Confidence Interval for Exp(B)	
				Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
Threshold	Very easy	-2.844	.4400	-3.706	-1.982	41.779	1	.000	.058	.025	.138
	Easy	-1.325	.2660	-1.846	-.803	24.796	1	.000	.266	.158	.448
	Somewhat Easy	-.171	.2270	-.616	.274	.567	1	.452	.843	.540	1.315
	Neither easy, nor difficult	.200	.2257	-.243	.642	.784	1	.376	1.221	.785	1.901
	Somewhat difficult	1.433	.2529	.937	1.929	32.101	1	.000	4.191	2.553	6.880
	Difficult	2.871	.3464	2.192	3.550	68.699	1	.000	17.660	8.956	34.822
Choice conflicts		.035	.0121	.011	.059	8.437	1	.004	1.036	1.011	1.060

Dependent Variable: Perceived Decision Difficulty

Model: (Threshold), Choice conflicts

Threshold = Very difficult decision (level 7 on scale).

E5. Hypothesis H_{4A} test – Chapter 5.3.4.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	45.885	1	.000
Choice conflicts	298.821	1	.000
Akaike's Information Criterion (AIC)			527.631

Dependent Variable: Information search effort

Model: (Intercept), Choice conflicts

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test			Exp(B)	95% Wald Confidence Interval for Exp(B)	
			Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
(Intercept)	.449	.0663	.319	.579	45.885	1	.000	1.567	1.376	1.784
Choice conflicts	.035	.0020	.031	.039	298.821	1	.000	1.036	1.032	1.040

Dependent Variable: Information search effort

Model: (Intercept), Choice conflicts

E6. Hypothesis H_9 test – Chapter 5.4.1

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	28.417	1	.000
Perceived decision difficulty	10.335	4	.035
Akaike's Information Criterion (AIC)			23.856

Dependent Variable: Shopping (1=Buy/0=Abandon)

Model: (Intercept), Perceived decision difficulty corrected for quasi-separation (transofrmed from 1-7 to 1-5 scale)

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test			Exp(B)	95% Wald Confidence Interval for Exp(B)	
			Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
(Intercept)	-.405	.5270	-1.438	.628	.592	1	.442	.667	.237	1.873
Very Easy	-1.204	1.2156	-3.587	1.179	.981	1	.322	.300	.028	3.250
Easy	-2.367	.7949	-3.925	-.809	8.867	1	.003	.094	.020	.445
Neither easy, nor difficult	-2.159	1.1639	-4.441	.122	3.442	1	.064	.115	.012	1.129
Difficult	-1.511	.6265	-2.739	-.284	5.821	1	.016	.221	.065	.753
Very Difficult	0[a]	.	.	.	.	.	.	1	.	.

Dependent Variable: Shopping (1=Buy/0=Abandon)

Model: (Intercept), Perceived decision difficulty corrected for quasi-separation (transofrmed from 1-7 to 1-5 scale)

a. Set to zero because this parameter is the reference.

E7. Hypothesis H_{1B} test – Chapter 5.4.2

ANOVA

Perceived Decision Difficulty

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	22.411	2	11.205	4.322	.015
Within Groups	417.394	161	2.593		
Total	439.805	163			

Post Hoc Tests

Multiple Comparisons

Dependent Variable: Perceived Decision Difficulty

Bonferroni

(I) Attribute Alignment	(J) Attribute Alignment	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Not Aligned	Control	-.636	.306	.117	-1.38	.10
	Aligned	-.885*	.311	.015	-1.64	-.13
Aligned	Control	.249	.307	1.000	-.49	.99
	Not Aligned	.885*	.311	.015	.13	1.64

*. The mean difference is significant at the 0.05 level.

E8. Hypothesis H_8 test – Chapter 5.4.2

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
Information search effort	7.004	1	.008
Akaike's Information Criterion (AIC)			148.926

Dependent Variable: Perceived Decision Difficulty

Model: (Threshold), Information search effort

Parameter Estimates

Parameter		B	Std. Error	95% Wald Confidence Interval		Hypothesis Test			Exp(B)	95% Wald Confidence Interval for Exp(B)	
				Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
Threshold	Very easy	-2.907	.4372	-3.764	-2.050	44.204	1	.000	.055	.023	.129
	Easy	-1.393	.2604	-1.904	-.883	28.637	1	.000	.248	.149	.414
	Somewhat easy	-.245	.2188	-.674	.184	1.255	1	.263	.783	.510	1.202
	Neither easy, nor difficult	.124	.2169	-.301	.549	.327	1	.568	1.132	.740	1.732
	Somewhat difficult	1.356	.2440	.877	1.834	30.875	1	.000	3.879	2.405	6.257
	Difficult	2.794	.3397	2.128	3.459	67.631	1	.000	16.339	8.396	31.797
Information search effort		.143	.0541	.037	.249	7.004	1	.008	1.154	1.038	1.283

Dependent Variable: Perceived Decision Difficulty

Model: (Threshold), Information search effort

Threshold = very difficult level 7 on the scale

E9. Hypothesis H_6 test - Chapter 5.5.2

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	.000	1	.998
Task Scenario	8.000	1	.005
Alternative search	13.796	1	.000
Task Scenario * Alternative Search	10.595	1	.001
Akaike's Information Criterion (AIC)			693.511

Dependent Variable: Information search effort
Model: (Intercept), Task Scenario (priming/no priming for maximization), Alternative search Maximization Inventory subscale, Interaction effect: Task Scenario * Alternative search

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test			Exp(B)	95% Wald Confidence Interval for Exp(B)	
			Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
(Intercept)	-.826	.3952	-1.600	-.051	4.365	1	.037	.438	.202	.950
Not primed	1.653	.5844	.508	2.799	8.000	1	.005	5.223	1.661	16.421
Primed for maximization	0[a]	.	.	.	.	.	.	1	.	.
Alternative search	.380	.0721	.238	.521	27.730	1	.000	1.462	1.269	1.684
Not primed * Alternative search	-.355	.1090	-.568	-.141	10.595	1	.001	.701	.566	.868
Primed * Alternative search	0[a]	.	.	.	.	.	.	1	.	.

Dependent Variable: Information search effort
Model: (Intercept), Task Scenario (priming/no priming for maximization), Alternative search Maximization Inventory subscale, Interaction effect: Task Scenario * Alternative search
a. Set to zero because this parameter is the reference.

References

Alba, J., Lynch, J., Weitz, B., Janiszewski, C., Lutz, R., Sawyer, A., & Wood, S. (1997). Interactive home shopping: consumer, retailer, and manufacturer incentives to participate in electronic marketplaces. *The Journal of Marketing*, 38-53.

Altman, M., Gill, J., & McDonald, M. P. (2004). *Numerical issues in statistical computing for the social scientist* (Vol. 508): John Wiley & Sons.

Anderson, C. (2006). *The Long Tail: Why the Future of Business Is Selling More for Less*. New York, NY: Hyperion.

Ariely, D., & Jones, S. (2008). *Predictably irrational*: HarperCollins New York.

Ayal, S., & Hochman, G. (2009). Ignorance or integration: The cognitive processes underlying choice behavior. *Journal of Behavioral Decision Making, 22*(4), 455-474.

Baymard Institute (2014). 29 Cart Abandonment Rate Statistics. Retrieved from http://baymard.com/lists/cart-abandonment-rate

Bearden, W. O., & Netemeyer, R. G. (1999). *Handbook of marketing scales: Multi-item measures for marketing and consumer behavior research*: Sage.

Beatty, S. E., & Smith, S. M. (1987). External search effort: An investigation across several product categories. *Journal of consumer research*, 83-95.

Bettman, J. R., & Park, C. W. (1980). Effects of prior knowledge and experience and phase of the choice process on consumer decision processes: A protocol analysis. *Journal of consumer research*, 234-248.

Botti, S., & Hsee, C. K. (2010). Dazed and confused by choice: How the temporal costs of choice freedom lead to undesirable outcomes. *Organizational Behavior and Human Decision Processes, 112*(2), 161-171. doi:http://dx.doi.org/10.1016/j.obhdp.2010.03.002

Chan, A., Dodd, J., & Stevens, R. (2004). The efficacy of pop-ups and the resulting effect on brands-A white paper by bunnyfoot Universality. *White Paper*.

Chartrand, T. L., & Bargh, J. A. (1996). Automatic activation of impression formation and memorization goals: Nonconscious goal priming reproduces effects of explicit task instructions. *Journal of personality and social psychology, 71*(3), 464.

Chernev, A., Böckenholt, U., & Goodman, J. (2015). Choice overload: A conceptual review and meta-analysis. *Journal of Consumer Psychology, 25*(2), 333-358.

Close, A. G., Kukar-Kinney, M., & Benusa, K. (2012). Towards a Theory of Consumer Electronic Shopping Cart Behavior: Motivations of E-Cart Use and Abandonment. *ONLINE CONSUMER BEHAVIOR: THEORY AND RESEARCH IN SOCIAL MEDIA, ADVERTISING, AND E-TAIL, Angeline G. Close, ed., Routledge*.

Cohen, J. (2013). *Statistical power analysis for the behavioral sciences*: Academic press.

Dar-Nimrod, I., Rawn, C. D., Lehman, D. R., & Schwartz, B. (2009). The Maximization Paradox: The costs of seeking alternatives. *Personality and Individual Differences, 46*(5–6), 631-635. doi:http://dx.doi.org/10.1016/j.paid.2009.01.007

Darby, M. R., & Karni, E. (1973). Free competition and the optimal amount of fraud. *Journal of law and economics*, 67-88.

DataScraping. (2015). Chart: count of products in amazon.com for major categorie. Retrieved from https://learn.scrapehero.com/chart-count-of-products-in-amazon-us-for-major-categories/

Dean, C. B. (1992). Testing for overdispersion in Poisson and binomial regression models. *Journal of the American Statistical Association, 87*(418), 451-457.

Dhar, R. (1997). Consumer preference for a no-choice option. *Journal of consumer research, 24*(2), 215-231.

Dhar, R., & Nowlis, S. M. (2004). To buy or not to buy: Response mode effects on consumer choice. *Journal of Marketing Research, 41*(4), 423-432.

Dooley, K. (2001). *Social research methods.* Paper presented at the 4 th ed. Upper Saddle River, NJ.

Ecommerce-News. (2015). Ecommerce in The Netherlands. Retrieved from http://ecommercenews.eu/ecommerce-per-country/ecommerce-the-netherlands/

Edwards, M. L., & Smith, B. C. (2011). The effects of the neutral response option on the extremeness of participant responses. *Incite, 6*.

Egeln, L. S., & Joseph, J. A. (2012). Shopping cart abandonment in online shopping. *Atlantic Marketing Journal, 1*(1), 1.

eMarketer. (2013). Ecommerce Sales Topped $1 Trillion for First Time in 2012 Retrieved from http://www.emarketer.com/Article/Ecommerce-Sales-Topped-1-Trillion-First-Time-2012/1009649

eMarketer. (2015). B2C e-commerce sales worldwide from 2012 to 2018 (in billion U.S. dollars). Retrieved from http://www.statista.com/statistics/261245/b2c-e-commerce-sales-worldwide/

Ericsson, A. K., & Simon, H. A. (1998). How to study thinking in everyday life: Contrasting think-aloud protocols with descriptions and explanations of thinking. *Mind, Culture, and Activity, 5*(3), 178-186.

Ericsson, K. A., & Simon, H. A. (1993). Protocol analysis verbal reports as data. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&scope=site&db=nlebk&db=nlabk&AN=1761

Fernandes, B. (2012). *Abandoning the Online Shopping Cart before Finalizing the purchase: influences form attitudes, subjective norms and internet experience.* Universidade Católica Portuguesa.

Fiedler, S., & Glöckner, A. (2012). The dynamics of decision making in risky choice: an eye-tracking analysis. *Frontiers in Psychology, 3*.

Fredrickson, B. L., & Kahneman, D. (1993). Duration neglect in retrospective evaluations of affective episodes. *Journal of personality and social psychology, 65*(1), 45.

Galetzka, M., Verhoeven, J. W., & Pruyn, A. T. H. (2006). Service validity and service reliability of search, experience and credence services: A scenario study. *International Journal of Service Industry Management, 17*(3), 271-283.

Gati, I., & Tversky, A. (1982). Representations of qualitative and quantitative dimensions. *Journal of Experimental Psychology: Human Perception and Performance, 8*(2), 325.

Gentner, D., & Markman, A. B. (1994). Structural alignment in comparison: No difference without similarity. *Psychological science, 5*(3), 152-158.

Google, I. M. (2014). The 2014 traveler's road to decision. Retrieved from https://www.thinkwithgoogle.com/research-studies/2014-travelers-road-to-decision.html

Groot, A. D., & Spiekerman, J. A. (1969). *Methodology: Foundations of inference and research in the behavioral sciences*: Mouton Amsterdam/Berlin/New York.

Hehman, E., Stolier, R. M., & Freeman, J. B. (2015). Advanced mouse-tracking analytic techniques for enhancing psychological science. *Group Processes & Intergroup Relations, 18*(3), 384-401.

Henneberry, R. (2012). 9 Ways To Decrease Shopping Cart Abandonment On Your eCommerce Website. Retrieved from http://blog.crazyegg.com/2012/08/14/decrease-shopping-cart-abandonment/

Highhouse, S. E., Diab, D. L., & Gillespie, M. A. (2008). Are maximizers really unhappy? The measurement of maximizing tendency. *Judgment and Decision Making Journal, 3*(5), 364.

Howard, J. A., & Sheth, J. N. (1969). *The theory of buyer behavior* (Vol. 14): Wiley New York.

Iyengar, S. S., & Lepper, M. R. (2000). When choice is demotivating: Can one desire too much of a good thing? *Journal of personality and social psychology, 79*(6), 995.

Iyengar, S. S., Wells, R. E., & Schwartz, B. (2006). Doing better but feeling worse looking for the "best" job undermines satisfaction. *Psychological Science, 17*(2), 143-150.

Jing, X. U., Zixi, J., & Dhar, R. (2013). Mental Representation and Perceived Similarity: How Abstract Mindset Aids Choice from Large Assortments. *Journal of Marketing Research (JMR), 50*(4), 548-559. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=bsh&AN=90046036&site=ehost-live

Joachims, T., Granka, L., Pan, B., Hembrooke, H., & Gay, G. (2005). *Accurately interpreting clickthrough data as implicit feedback.* Paper presented at the Proceedings of the 28th annual international ACM SIGIR conference on Research and development in information retrieval.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the Econometric Society*, 263-291.

Kokonendji, C. C., Demétrio, C. G. B., & Dossou-Gbété, S. (2003). *Overdispersion and Poisson-Tweedie exponential dispersion models.* Paper presented at the VIII Journées Zaragoza-Pau de Mathématiques Appliquées et de Statistiques: Jaca, Spain, September 15-17, 2003.

Kooti, F., Lerman, K., Aiello, L. M., Grbovic, M., Djuric, N., & Radosavljevic, V. (2015). Portrait of an Online Shopper: Understanding and Predicting Consumer Behavior. *arXiv preprint arXiv:1512.04912*.

Kukar-Kinney, M., & Close, A. (2010). The determinants of consumers' online shopping cart abandonment. *Journal of the Academy of Marketing Science, 38*(2), 240-250. doi:10.1007/s11747-009-0141-5

Luce, M. F., Bettman, J. R., & Payne, J. W. (2001). Emotional decisions: Tradeoff difficulty and coping in consumer choice. *Monographs of the Journal of Consumer Research*, 1-209.

Macdonald, M. (2013). Why Online Retailers Are Losing 67.45% of Sales and What to Do About It. Retrieved from https://www.shopify.com/blog/8484093-why-online-retailers-are-losing-67-45-of-sales-and-what-to-do-about-it

Markman, A. B., & Medin, D. L. (1995). Similarity and alignment in choice. *Organizational behavior and human decision processes, 63*(2), 117-130.

Moorthy, S., Ratchford, B. T., & Talukdar, D. (1997). Consumer information search revisited: Theory and empirical analysis. *Journal of consumer research*, 263-277.

Moshitch, D., & Nelken, I. (2014). Using Tweedie distributions for fitting spike count data. *J Neurosci Methods, 225*, 13-28. doi:10.1016/j.jneumeth.2014.01.004

Moshrefjavadi, M. H., Dolatabadi, H. R., Nourbakhsh, M., Poursaeedi, A., & Asadollahi, A. (2012). An analysis of factors affecting on online shopping behavior of consumers. *International Journal of Marketing Studies, 4*(5), p81.

Najafi, I. (2014). A Study on the Effect of Electronic Trust Factors on the Success of B2C E-Commerce–Improvement of Conversion Rate Index (A case study of six online retailer companies in the city of Mashhad, Iran, 2011-2012).

Navalpakkam, V., & Churchill, E. (2012). *Mouse tracking: measuring and predicting users' experience of web-based content.* Paper presented at the Proceedings of the SIGCHI Conference on Human Factors in Computing Systems.

Nelson, P. (1970). Information and consumer behavior. *The Journal of Political Economy*, 311-329.

Nielsen, J. (1999). *Designing web usability: The practice of simplicity*. Indianapolis: New Riders Publishing.

Nielsen, J. (2005). Authentic behavior in user testing: Jakob Nielsen's Alertbox.

Odekerken-Schröder, G., & Wetzels, M. (2003). Trade-offs in Online Purchase Decisions:: Two Empirical Studies in Europe. *European Management Journal, 21*(6), 731-739.

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1988). Adaptive strategy selection in decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 14*(3), 534.

Rim, H. B., Turner, B. M., Betz, N. E., & Nygren, T. E. (2011). Studies of the dimensionality, correlates, and meaning of measures of the maximizing tendency. *Judgment and Decision Making, 6*(6), 565-579.

Rodden, K., Fu, X., Aula, A., & Spiro, I. (2008). *Eye-mouse coordination patterns on web search results pages.* Paper presented at the CHI'08 Extended Abstracts on Human Factors in Computing Systems.

Ropers, D. (2014). *Bol.com Financial Analysis report*. Retrieved from http://bit.ly/1DO3vKc

Salvendy, G. (2012). *Handbook of human factors and ergonomics*: John Wiley & Sons.

Scheibehenne, B., Greifeneder, R., & Todd, Peter M. (2010). Can There Ever Be Too Many Options? A Meta-Analytic Review of Choice Overload. *Journal of Consumer Research, 37*(3), 409-425. doi:10.1086/651235

Schultz, D. E., & Block, M. P. (2015). U.S. online shopping: Facts, fiction, hopes and dreams. *Journal of Retailing and Consumer Services, 23*(0), 99-106. doi:http://dx.doi.org/10.1016/j.jretconser.2014.10.010

Schwartz, B. (2004). The tyranny of choice. *SCIENTIFIC AMERICAN-AMERICAN EDITION-, 290*(4), 70-75.

Schwartz, B., Ward, A., Monterosso, J., Lyubomirsky, S., White, K., & Lehman, D. R. (2002). Maximizing versus satisficing: happiness is a matter of choice. *J Pers Soc Psychol, 83*(5), 1178-1197.

Shafir, E., Simonson, I., & Tversky, A. (1993). Reason-based choice. *Cognition, 49*(1), 11-36.

Statista. (2015). Online shopping cart abadonment statistics. Retrieved from http://www.statista.com/statistics/232285/reasons-for-online-shopping-cart-abandonment/

Thomas, B., Dean, E., Smith, K., & Thatcher, N. (2014). Holiday Is (Almost) Here: 5 Shopping Trends Marketers Should Watch. Retrieved from https://www.thinkwithgoogle.com/articles/five-holiday-shopping-trends-marketers-should-watch.html

Turner, B. M., Rim, H. B., Betz, N. E., & Nygren, T. E. (2012). The Maximization Inventory: Society for Judgment and Decision Making.

Tversky, A. (1972). Elimination by aspects: A theory of choice. *Psychological review, 79*(4), 281.

Tversky, A., & Shafir, E. (1992). Choice Under Conflict: The Dynamics of Deferred Decision. *Psychological Science, 3*(6), 358-361. doi:10.1111/j.1467-9280.1992.tb00047.x

Urbany, J. E., Dickson, P. R., & Wilkie, W. L. (1989). Buyer uncertainty and information search. *Journal of consumer research*, 208-215.

Van Den Haak, M., De Jong, M., & Jan Schellens, P. (2003). Retrospective vs. concurrent think-aloud protocols: testing the usability of an online library catalogue. *Behaviour & information technology, 22*(5), 339-351.

van den Haak, M. J. (2008). A penny for your thoughts. Investigating the validity and reliability of think-aloud protocols for usability testing.

Wakita, T., Ueshima, N., & Noguchi, H. (2012). Psychological distance between categories in the likert scale comparing different numbers of options. *Educational and Psychological Measurement, 72*(4), 533-546.

Waters, C. K. (2007). The nature and context of exploratory experimentation: An introduction to three case studies of exploratory research. *History and philosophy of the life sciences*, 275-284.

Weijters, B., Cabooter, E., & Schillewaert, N. (2010). The effect of rating scale format on response styles: The number of response categories and response category labels. *International Journal of Research in Marketing, 27*(3), 236-247.

Wilson, T. D. (1999). Models in information behaviour research. *Journal of documentation, 55*(3), 249-270.

Xu, Y., & Huang, J.-S. (2015). Factors influencing cart abandonment in the online shopping process. *Social Behavior and Personality: an international journal, 43*(10), 1617-1627.

Zhang, S., & Fitzsimons, G. J. (1999). Choice-Process Satisfaction: The Influence of Attribute Alignability and Option Limitation. *Organizational Behavior and Human Decision Processes, 77*(3), 192-214. doi:http://dx.doi.org/10.1006/obhd.1999.2821

Zuur, A. F., Ieno, E. N., & Elphick, C. S. (2010). A protocol for data exploration to avoid common statistical problems. *Methods in Ecology and Evolution, 1*(1), 3-14. doi:10.1111/j.2041-210X.2009.00001.x