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WHEN DATA CHANGES PRE-PURCHASE BEHAVIOR: THE EFFECTS OF INFORMATION VISUALIZATION ON ONLINE INFORMATION SEEKING

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Tese de Doutorado apresentada ao Programa de Pós-Graduação em Administração da Universidade Federal do Rio Grande do Sul, como requisito parcial para a obtenção do grau de Doutor em Administração.

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This work is dedicated to my parents
and to my best friends.

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ABSTRACT

Online consumer information search became a crucial initial step in the purchase decision process. The objective of this dissertation is to investigate and measure the effects of different visual representations of information about products on individual's behavior during pre-purchase online information seeking activities. More specifically, this dissertation analyze what type of information customers considered most important and pays more attention and what is the extent of the visual aspect and its impact in information seeking behavior. To do so, five experiments were conducted, three using online participants via Amazon Mechanical Turk, and two using participants in a laboratory setting, being collected biological measures in one of them. Through two studies, the first article shows how different degrees of evaluability of the same online review can influence on helpfulness, overestimation of information, and purchase intention. It also evidence individual's involvement while browsing has a moderating role in the relation between evaluability and helpfulness as well as in the relation between evaluability and purchase intention. The second article analyze the relationship between depth-of-field and type of search on several behavioral outcomes, such as intention do revisit the website and visual appeal. It was also investigated whether or not involvement, expertise and attitude toward products moderates these relations. Drawing on the findings of the first and second articles, the third article focus on replicate the finding of the second article via biological measures using an eye-tracking device, including attention measures. The third article aims to contribute to online information seeking literature by investigating participant's online search and browse behaviors and the resulting processing of information when viewing products presented visually differently in a webpage. These patterns of individual's visualization studied in both three articles have important practical implications for the website design creating experiences that supports the type of information search undertaken by consumers.

Keywords: *Pre-purchase Information Seeking; Eye-tracking; E-commerce; Information Visualization*

RESUMO

A busca por informações de consume online tornou-se um passo crucial no processo de decisão de compra. O objetivo desta tese é investigar e medir os efeitos de diferentes representações visuais de informações sobre produtos no comportamento individual durante a busca por informações pré-compra na internet. Mais especificamente, esta tese analiza que tipo de informação os clients consideram mais importantes, prestam mais atenção e qual o impacto do aspect visual no comportamento de busca por informações. Para atingir este objetivo, cinco experimentos foram conduzidos, três usando participantes por coleta online, através da ferramenta Amazon Mechanical Turk e dois experimentos em um ambiente de laboratório, sendo que em um deles foram utilizadas medidas biológicas. Através de dois estudos, o primeiro artigo mostra como diferentes níveis de *evaluability* de uma mesma *review* escrita por clients sobre determinado produto pode influenciar em *helpfulness, overestimation of information,* e intenção de compra. O artigo também evidencia que o envolvimento individual enquanto o indivíduo busca informações tem um papel moderador na relação entre *evaluability* e *helpfulness*, além de influenciar, também, a relação entre *evaluability* e intenção de compra. O segundo artigo analiza o relacionamento entre *depth-of-field* e tipo de busca por informações em diversas variáveis dependentes, tais quais: intenção de revisitar o website e *visual appeal.* Também investiga-se se envolvimento, *expertise* e attitude em relação ao produto pode moderar essas relações. A partir do estudado no primeiro e segundo artigos, o terceiro artigo procura replicar os achados do segundo artigo através de medidas biológicas, utilizando um equipamento de *eye-tracking*, incluindo-se medidas de atenção. O ultimo artigo busca contribuir para a literatura sobre busca de informações online a partir de uma investigação do comportamento de busca por informações (tanto em tarefas de *browsing* quanto em tarefas específicas) e o processo de informações quando são apresentadas informações sobre o produto de forma visualmente diferentes. Estes padrões de visualização individual estudados nos três artigos têm importantes implicações práticas para o *design* de websites, fazendo com que se aperfeiçoem experiências que suportem o tipo de informação buscada pelos consumidores.

***Palavras-chave**: Busca por informações pré-compra; Eye-tracking; Comércio Eletrônico; Visualização da Informação*

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Summary

CHAPTER 1

Introduction

In 1971, Herbert Simon said “in an information-rich world, the wealth of information creates a poverty of attention and a need to allocate that attention efficiently among the overabundance of information sources that might consume it”, when attempting to understand the impact of the large volume of information available (Simon, 1971). Nevertheless, what the author likely did not realize is that this "wealth of information" and the numerous "information sources" used today would be present in such a large scale, even in a single webpage.

Information visualization and visual representations are a contemporary issue that deserves special attention as the volume of information available to the individual increases. Several artifices for better viewing and processing of such information can be found in different contexts. Once the information is presented in different formats and with different attributes, the e-commerce context is found to be one of the most relevant (Jia, Shiv, Rao, 2014).

All this information available to consumers is growing, and the rate at which people and companies worldwide generate new data is also growing exponentially annually (Siegel, 2013). Moreover, it is currently expected that we produce about ten times more data/year than the amount we used to produce ten years ago (Agrawala, Li, Berthouzoz, 2011). However, for Lurie (2004), Schwarts (2004), and many other authors, the benefits of all this information are often unrealized because consumers are increasingly overloaded with information in electronic environments.

Extensive research on Information Visualization, referred to as InfoVis as suggested by Manovich (2011), appears in the Information Systems and Marketing literature (Isenberg *et al.,* 2013; Agrawala, Li, Berthouzoz, 2011; Ziemkiewicz *et al.,* 2012) and attempts to deal with this consequence. Furthermore, studies regarding best ways to present all this information are currently being developed and published in the top journals from Information Systems and Marketing fields, as indicated, respectively, by AIS (“basket” of eight top IS journals from the Association for Information Systems, 2016) and AMS (Academy of Marketing Science, 2016).

Accordingly to that, Lurie and Mason (2007) argue that humans also have evolved great visual and spatial skills, including the ability to detect edges and discontinuities, things that are distinct, variations in color and shape, and motion. This is not only for interactive visualizations but also to recognize patterns and to retrieve information using visual cues. The researchers also state that visual representations can enlarge problem-solving capabilities by enabling more data processing without overloading consumers.

Thus, the goal of visualization is to aid our understanding of data by leveraging the human visual system's highly tuned ability to see patterns, spot trends, and identify outliers (Heer, Bostock, Ogievetsky, 2010). Thus, further dialogue is necessary between researchers on visualization, human-computer interaction, computer-supported cooperative work, and other related fields. Such dialogue can help to more strongly communicate information's value to community (Isenberg *et al.,* 2013).

For Agrawala, Li and Berthouziz (2011), the problem is that human designers lack the time to hand-design effective visualizations for that wealth of data. Too often, data are either poorly visualized or not visualized at all. For these researchers, evaluation criteria can quantify the effectiveness of some aspect of the visualization, which enables the assessing of the overall effectiveness of visualization by considering a set of evaluation criteria covering all major visual design aspects. Many other information domains could benefit from a deeper understanding of the means visual-display techniques affect the perception and cognition of information (Agrawala, Li, Berthouzoz, 2011).

Insofar, the precise visual mechanism of a change in perceptual focus remains an open question (Jia, Shiv and Rao, 2014). Most of the related work does not address how users and consumers think or how to apply visualizations as an extension of an individual's cognitive ability. Each of us has aspects that differentiate us from everyone else. Our experiences, personality, and cognitive abilities influence our approach to performing a task and our understanding of a problem domain. Cognitive-psychology research has shown that such differences can significantly impact a user's dexterity with an interface or a tool. Although these findings remain at an early stage, they suggest that we should not study visualization in a vacuum but in the context of differences among its users. This, in turn, could lead to a shift in how we evaluate and design visualizations for different user groups, tasks, and domains (Ziemkiewicz *et al.,* 2012).

The massive quantity of information available to consumers at the decision point (and here we start to include the e-commerce context), for instance, can lead to information overload, which can result in a greater reliance on heuristics and a greater susceptibility to biases in economic decision making. Vendors or service providers also face the problem of needing to analyze in real-time massive quantities of information; in addition, vendors or service providers tend to ignore the cognitive bias effects on consumers.

Jia, Shiv and Rao (2014), for instance, suggest future investigations using eye-tracking or implicit measures of visual attention and using gaze to explore the precise changes in visual scrutiny that may underlie such effect. This is important for knowing the exact path of visual inspection of participants in a research study, or when perceptual focus switches.

For some products, a switch in perceptual focus essentially reduces the focus on the aspects on which the products are differentiated. Without visual differentiation on the perceptual level on which they are defined, products will lose their distinctiveness, desirability, and lasting appeal and become homogenous (Jia, Shiv and Rao, 2014).

Such design connects the visual aspect of the visualization with consumer's perception and cognition of the underlying information the visualization is meant to convey. In some cases, prior research in perception and cognition suggests or formalizes the appropriate design principles.

In line with these findings, this dissertation further explores the investigation and measure of effects of different visual representations concerning an e-commerce environment (clients reviews, products disposal) on individual's behavioral and biological outcomes during the pre-purchase online information seeking activities.

Specifically, this dissertation aims to: a) analyze what type of information customers considered most important and pay more attention when too much data are offered on an e-commerce website; b) analyze what is the extent of the visual aspect and its impact in information seeking process or tasks; and, c) investigate the moderating role of expertise, attitude toward products and involvement during the information seeking process.

So, the three following research questions motivate this dissertation: First, how visual representations are likely to affect pre-purchase online information seeking behavior, particularly those websites that involve the analysis or synthesis of substantial amounts of data? Second, what type of information did customers consider most important and pay more attention? And, finally, what is the extent of the visual aspect in this choice?

To answer these questions, this dissertation, which is composed of three essays, performs in total five experiments.

The first article, “Involvement Moderates the Relationship between Evaluability and Online Information Seeking Behavior”, discuss that online consumer information search became a crucial initial step in the purchase decision process. Through two studies, the article shows how different degrees of evaluability (the ease of which each information can be assessed and compared) of the same online review can influence on helpfulness, overestimation of information and purchase intention. It also evidence individual’s involvement while browsing has a moderating role in the relation between evaluability and helpfulness as well as in the relation between evaluability and purchase intention.

The second article, “The impact of depth-of-field and type of search on online consumer information search” aimed to analyze relationship between depth-of-field and type of search on several behavioral outcomes, such as intention do revisit the website and website’s visual appeal. It was also investigated whether or not involvement, expertise and attitude toward products moderates these relations.

Drawing on the findings of the first and second articles, the third article, “The Influence of Evaluability and Type of Search on Pre-Purchase Online Information Seeking: An Eye-Tracking Analysis” focuses on replicate the finding of the second article via repeated-measures and biological measures using an eye-tracking devices. Also, attention variables were included in the last article.

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CHAPTER 2

Article 1: "Involvement Moderates the Relationship between Evaluability and Online Information Seeking Behavior"

Co-author: Antonio Carlos Gastaud Maçada, Professor of MIS, UFRGS.

(To be presented in the 2016 AMS - Academy of Marketing Science World Marketing Congress)

2.1 Abstract

Online consumer information search became a crucial initial step in the purchase decision process. Through two studies, we found how different degrees of evaluability (the ease of which each information can be assessed and compared) of the same online review can influence on helpfulness, overestimation of information and purchase intention. We also found individual's involvement while browsing has a moderating role in the relation between evaluability and helpfulness as well as in the relation between evaluability and purchase intention.

Keywords: Evaluability, Involvement, Information Seeking, E-Commerce.

2.2 Introduction

Imagine yourself searching for or comparing any information about a product you are considering buying on an online store. After reading the product characteristics, you naturally decide to read the reviews to look for what other consumers are saying about the product. Then you convinced yourself about what you were in doubt and decide to acquire the product. Now, imagine yourself in the same situation, however, after analyzing the reviews, you decide not to buy the product.

The above circumstances may seem very different, but the same product and, mainly, the same information (attributes, valences, etc.) could be presented in both reviews, resulting in different levels of helpfulness, information overestimation and, also, the product's purchase or not. The only difference between these situations could be the visual presentation of this information.

Online retailers are being immersed in an information-rich environment, trying to present more information to customers but, probably, creating too much cognitive input, making difficult the effectively process of information. Thus, for tasks with a strong visual component, like an online purchase, cognitive fit theory and cognitive load theory seem to lead to diverging assumptions with respect to the possible contribution of environments to decision and performance (Van Der Land *et al.* 2013).

Related to this problem, the online consumer information search became a crucial initial step in the purchase decision process. For Pfeiffer et al. (2014), when choosing among alternatives, decision makers follow a decision strategy, which is defined as a set of operations used to transform an initial stage of knowledge into a final goal state of knowledge where the decision maker feels the decision problem is solved.

As in van der Land *et al.* (2013), the focus of this study is not on the process of learning and learning outcomes, concepts that are traditionally related to cognitive load theory. Instead, based on cognitive fit theory (CFT), we assume that visual elements on online retailers may support individual decision making since these environments are able to provide the visual cues that help individuals comprehend the nature and significance of various elements of the task.

Recent research finds that many factors may feed into different behaviors when searching for information online, and how visual elements are presented is one of the most important (Jia, Shiv and Rao, 2014; Kim, Albuquerque and Bronnenberg, 2011). Besides many previous research, none of them analyze how evaluability, defined by Lurie and Mason (2007) as the "ease with which information can be evaluated and compared", impacts on pre-purchase online behavior.

It also seems that past researches, like those based on Lurie and Mason (2007) model, have remained only in the purchase task *per se* (trying to show the impact of how a change in the product's information presentation is due to impact some of consumer's behaviors), and not considering some of the previous process, like the consumer information search for information.

In this research, we analyze the relationship between the way information from an online review can be assessed and compared (evaluability) with some behavioral measures, like helpfulness and overestimation of that information. In addition to this we evaluate if this relation can be moderated by people involvement during the search for information. Hence, we hypothesize that different levels of evaluability may impact on helpfulness, overestimation of information and purchase intention. We also hypothesize that these relations may be moderated by individual's involvement when browsing. In the Study 1 we tested the main effects of these relations. In the Study 2 we also analyzed the moderation role of involvement in these relations.

We found that different degrees of evaluation of the same online review can influence not only the purchase intention, but also how helpful consumers perceive that information to make a decision and how they overestimate (underestimate) the information presented in the review.

Next, we present the conceptual background used in this research by reviewing and approximating Cognitive Fit and Cognitive Load theories with the online information search. In this section we also present the concept of evaluability and how it is used in the context of this research. In the following section we present the first study, which evaluated the main effects of evaluability in the proposed outcomes. After, we present the Study 2, which aimed to retest the previous relations as well as to analyze to what extent Involvement can moderate these relations. Finally, conclusions and future directions for this research are presented.

2.3 Conceptual Background

2.3.1 Cognitive Fit and Cognitive Load Theories: How can they help to analyze online search for information?

Online retailers are being immersed in an information-rich environment, trying to present more information to customers but, probably, creating too much cognitive input, making difficult the effectively process of information. Thus, for tasks with a strong visual component, like an online purchase, cognitive fit theory and cognitive load theory seem to lead to diverging assumptions with respect to the possible contribution of environments to decision and performance (Van Der Land *et al.* 2013).

Human problem solving and its complex underlying cognitive processes have been extensively examined by researchers in cognitive psychology (Goswami, Chan, Kim, 2008; Shaft, Vessey, 2006; Agarwal, Sinha, Tanniru, 1996). Dull and Tegarden (1999) say from a cognitive science perspective, visualizations can improve problem-solving capabilities. In his seminal work, Miller (1956) describes a set of results that imply that a human's input channel capacity can be increased by using visual abilities. The results suggest that different parameters in the visual channel can be exploited to increase the amount of data that decision makers process without suffering information overload.

Cognitive Fit Theory (CFT) poses that a match between the way information is presented and individuals' tasks enhances task performance (Vessey, Galletta, 1991). Thus, in tasks where the visual element is important visual mechanisms may support some cognitive tasks like attention and information acquisition. Furthermore, CFT posits that if a match is realized between the individuals' tasks and visual presentation of information, this will lead to greater individual understanding regarding some products characteristics, for instance. According to information processing theory a person solving a problem seeks ways to reduce the problem solving effort, since he/she is a limited information processor. The method used to reduce the effort by matching the problem or task to its data representation is known as cognitive fit (Vessey, 1991).

The mental representation is the way the problem is represented in human working memory. When a data format fits for its use (representation and task are matching), more effective and efficient problem-solving performance is achieved. It can also be suggested that cognitive fit means higher representational information quality as described in information success models and thus has a positive effect on user satisfaction, creates benefits for the users, and increases user's intention to use the system (Urbaczewski, Koivisto, 2008).

Mahoney *et al.* (2003) say cognitive ability and the theory of cognitive fit are naturally linked in the decision-making process. Cognitive ability addresses how the decision process works, and the theory of cognitive fit explore how data presentation affects the decision process. Cognitive fit research has shown that matching tasks with the appropriate support data display format enhances performance because the mental representation formulated is consistent with the task. Matching task and data display format increases the decision-maker's time and/or accuracy (Mahoney *et al.*, 2003; Agarwal, Sinha, Tanniru, 1996).

However, on the other hand, Cognitive Load Theory (CLT) states that learners' cognitive capacity may be overloaded by the richness of some visual environments (Land *et al.* 2013). Cognitive load theory is related with the amount of mental energy required to processing a given volume of information. The major factor that contributes to cognitive load is the number of elements that need to be attended to (Sweller, 1994).

Van der Land *et al.* (2013), say CLT is especially relevant in light of the fact that reaching a shared understanding requires the rapid transmission and exchange of less detailed information (interaction), as opposed to the slow, in-depth processing required for individual understanding. At the center of cognitive load theory is the human memory system, in particular the relationship between limited working memory and unlimited long-term memory. Baddeley (1992) defined working memory as a brain system that provides temporary storage and manipulation of the information necessary for performance of complex cognitive tasks.

Our working memory makes it difficult for us to understand and process information that is presented to us simultaneously as this creates heavy cognitive loads upon the consumer/user. A consumer's attention could be focused by directing attention to the information that is most important or immediately relevant, through a technique called instructional cueing. To prevent the diversion of a user's attention, different element such as text, color, and sound can be used to reinforce a message (Lee, Lehman; 1993).

Homer, Plass and Blake (2008) say that one method of partially overcoming the limits of working memory is to present part of the information being taught in a visual mode and part of it in a verbal mode. There is considerable evidence that humans have two separate working-memory systems, or channels: one for processing visual or pictorial information, and one for processing auditory or verbal information (Baddeley, 1986). Because each system has a relatively limited capacity, it is easy for a system to become overloaded if more than a few chunks of novel information are processed simultaneously (Baddeley, 1986; Miller, 1956; Sweller, 2003).

For Mostyn (2012), an important advantage of the theory has been the capacities to empirically replicate studies that describe the human cognitive process such that general principles can be developed that apply in a wide variety of instructional applications. In addition to acquiring knowledge about a domain (i.e., declarative knowledge), an individual must also acquire knowledge about the necessary skills and strategies to complete the task (procedural knowledge) (Williams, Noyes, 2007).

As in van der Land *et al.* (2013), the aim of using CFT and CLT in this study as a background is not on the process of learning and learning outcomes, concepts that are traditionally related to cognitive load theory. Instead, based on cognitive fit theory, we assume that changes in how information can be assessed and compared may support individual decision making since e-commerce environments are able to provide the visual cues that help individuals comprehend the nature and significance of various elements of the tasks.

Using the background from both theories, we want explore in this research to what extent different levels of evaluability can impact in the proposed outcomes. For example, will a tabular representation of a textual online review lead to greater levels of helpfulness? Will customers overestimate this information? Following one of the recommendations from Lurie and Mason (2007), the concept of evaluability, described next, has been applied to evaluate this relation.

2.3.2 Evaluability

A theoretical model, developed by Lurie & Mason (2007), advances that two different dimensions of visual representation, namely information context (IC) and visual perspective (VP), have an impact on decision processes or tasks. The first dimension refers to how the information is presented and is determined by variables such as data values, colors, and shapes specific to a given task. The second refers on how this information can be manipulated by the user (e.g. interaction).

It is possible to evaluate the impact of these dimensions on some task by identifying information visualization representations related to those dimensions and then, measure differences in process and outcomes using some dissimilarity. Some examples previously presented by literature about how to assess these dimensions in order to see changes in outcomes includes the possibility of grouping and moving selected objects into focus, prune information from display, the ability to make comparisons and assessments of trends and associations in the data.

For Lurie and Mason (2007), evaluability refers to the ease with which information can be evaluated and compared. By making it simpler to compare information, visualization tools enable decision makers to notice changes, recognize outliers, and observe patterns more quickly (Hsee 1996). Making information easier to compare is likely to lead to increased acquisition, weighting, and processing of this information (Ariely and Lynch 2000; Jarvenpaa, 1990).

Although practitioners frequently state that information visualization leads to improved, faster, and more assured decisions (Brath and Peters 2005), whether graphic or textual presentations are superior likely depends on the fit between these alternative representations and the nature of the task (Vessey 1991).

Some tasks include those that focus on discrete data values. Although the same information is presented, graphic presentations enhance the evaluability of spatial information, whereas tables enhance the evaluability of symbolic information (Vessey 1991). Graphic representations are likely to be superior for detecting trends, comparing patterns, and interpolating values. In contrast, tabular representations are superior for retrieving specific data values (Jarvenpaa and Dickson 1988; Vessey 1991). Displays that combine both tabular and graphic information may lead to better performance than either graphic or tabular displays alone (Benbasat 1986).

This suggests that, in evaluating and choosing products, decision makers will use more attributes and engage in more compensatory decision processes when information is presented graphically. In addition, because interactions between features are more readily detected in graphic displays than in verbal descriptions, the relative strength of such interactions is likely to be stronger for graphic than for text information (Lurie and Mason, 2007; Holbrook and Moore, 1981).

Evaluability concept is being studied in the fields of visualization and decision making in the web contexts but mainly when the product is the focus. As the use of reviews is increasing and it is gaining importance to decision-making, studying the way these reviews are presented may give more insights to customers and returns to the web store. In the studies that will be presented next, we try to show how manipulations in the visual aspects of the reviews can impact in some behavioral outcomes, like how helpful were the review for participants to decide, if they overestimate one or other kind of information and their purchase intention after reading the reviews. Also, we analyze how costumer involvement can play a moderating role in these relations.

2.4 Experiment 1: The effects of evaluability on helpfulness, purchase intention and overestimation of information

In this study we aim to discuss to what extent evaluability can impact on helpfulness, purchase intention and overestimation of information when searching for information on an online store, more specifically, when reading online reviews made by other costumers. To analyze that, we designed a single-factor experiment to address its main effects.

2.4.1 Method

2.4.1.1 Design and Participants

A between-subjects single factor design (Evaluability: Textual Information, *T;* Graphic Information, *G;* and Both, *B*) was performed. The variable was manipulated to reflect the definition of evaluability according to Lurie and Mason (2007). Data were collected through Qualtrics and Amazon Mechanical Turk (N = 65, 41 men; mean age = 30) with participants from the United States.

As a prerequisite all participants should have at least 95% of approval in previous HITs and not having answered before the pre-test questionnaire.

2.4.1.2 Procedures

In the first screen participants were told they were participating and collaborating with an academic research. After, participants were given the following instructions: "Now, imagine you've been thinking about acquiring a new cell phone for personal use. Today you decided to access an online store to take a look in the products and, maybe, get yourself a new mobile. You enter the Amazon.com homepage and among plenty of cell phones available you have finally chosen a device which most fit to your needs. After, you decide to take into consideration what other consumers are saying about this product by reading reviews they wrote in the bottom of the page".

By clicking in the "next" button, participants were presented to one of the experimental conditions, which were composed only by the product's review, not mentioning neither the brand nor model and other characteristics. After reading the review, participants were invited to answer a brief questionnaire containing the scales. Then, some demographics information was collected and the debriefing was held.

2.4.1.3 Stimulus

As stimulus it was used a real product (cell phone) review extracted from Amazon.com website as the most helpful review of that product, ranked by own customers (one with good evaluation and the other with poor evaluation about the product). In the "Textual" condition, six positive and six negative information (attributes) extracted from this review were presented to participants in a single paragraph text, randomizing the order of the attributes.

In the "Graphic" condition, the same attributes were presented but now in a table containing two columns, one for "positive attributes" and other for "negative attributes". In this situation only the attributes were presented, omitting any other word presented in the sentences in the later condition. Again, the order of presentation of which column would be shown firstly was randomized.

Finally, in the last condition, "Both", we have used again the same attributes but half of them presented in a text format (like in the *T* condition) and the other half in a table (like in the *G* condition).

2.4.2 Results and Discussion

2.4.2.1 Helpfulness

A one-way ANOVA was conducted to explore how helpful were those information presented to participants using a scale from 1 to 5 (very unhelpful – very helpful, $\alpha = 0{,}791$). We observed a significant difference in levels between groups ($F(2, 62) = 14.05$, $p \leq 0.05$). Using Tukey HSD test we found that the average of the *T* group ($M = 4.67$) was significantly different from the *B* group ($M = 3.65$). The *B* group was also significantly different compared to the *G* group ($M = 4.65$). Comparisons between *G* and *T* groups showed no statistically significant difference.

2.4.2.2 Purchase Intention

A one-way ANOVA was conducted to explore how likely participants would purchase the cell phone after reading the reviews. We measured this using a single-item scale from 1 to 7 as in Netemeyer et *al.* (2004) (very unlikely – very likely). We observed a significant difference in levels between groups ($F(2, 62) = 7.54$, $p \leq 0.05$). Using Tukey HSD we found that the average of the *T* group ($M = 1.67$) was significantly different from the *G* group ($M = 4.33$). Comparisons between the other groups showed no statistically significant difference.

2.4.2.3 Overestimation of Information

It's also important to know if participants overestimate, or put more weight on positive or negative attributes. After measure the previously two variables, respondents were told to recall three attributes about the reviews. We, then, attributed weight to those recalls according to their valence ("+" for positive attributes and "–" for negative) ending up in a score. A one-way ANOVA was conducted using this score, presenting significant difference in levels between groups ($F(2, 62) = 18.5$, $p \leq 0.05$). Using Tukey HSD we found that the average of the *T* group ($M = -5.67$) was significantly different from the *B* group ($M = -1$). The G group ($M = 2.67$) was significantly different compared to the B group. Also, The *T* group was significantly different compared to the *G* group.

2.4.3 General Discussion

Analyzing the results for this study we found some important differences in means between some groups. When asking how helpful were the reviews for participants to decide, the mean for the group exposed to the *T* condition (where the review were presented only using text in a single paragraph, M = 4.67) was significantly different from the *B* group (where both textual and graphic information were presented in the same review, M = 3.65). Also, the *B* group was significantly different when compared to the *G* group (where the information were presented using a graphic visualization, M = 4.65). This led us to assume that people presented to textual and graphic reviews consider the information more helpful than those presented to reviews containing both presentations. Regarding the purchase intention, we only found significantly differences when comparing the *T* group (M = 1.67) and the *G* group (M = 4.33). People exposed to the graphic review are too much disposed to buy the product than people exposed to the textual condition.

Through these manipulations we can also see that consumers overestimate one or other kind of information depending on how this information is presented. Using Tukey HSD post-hoc tests we found that all groups are significantly different. When asked to recall some attributes presented in the review the most evident difference was when comparing the *T* group (M = -5.67) and the *G* group (M = 2.67). Participants allocated in the *T* group recall much more negative information or attributes presented in the review than the *G* group, for example, which recalled more positives than negative attributes.

2.5 Experiment 2: The moderating role of involvement

In the Study 2 we aimed to test again the relations presented in the Study 1, as well as to analyze to what extent Involvement can moderate these relations.

For Lurie and Swaminathan (2009), involvement may play a moderating role because many visualization tools require user effort. Unless the decision is sufficiently important, the user may be unwilling to engage in the cognitive and physical effort needed to realize the full benefits.

2.5.1 Method

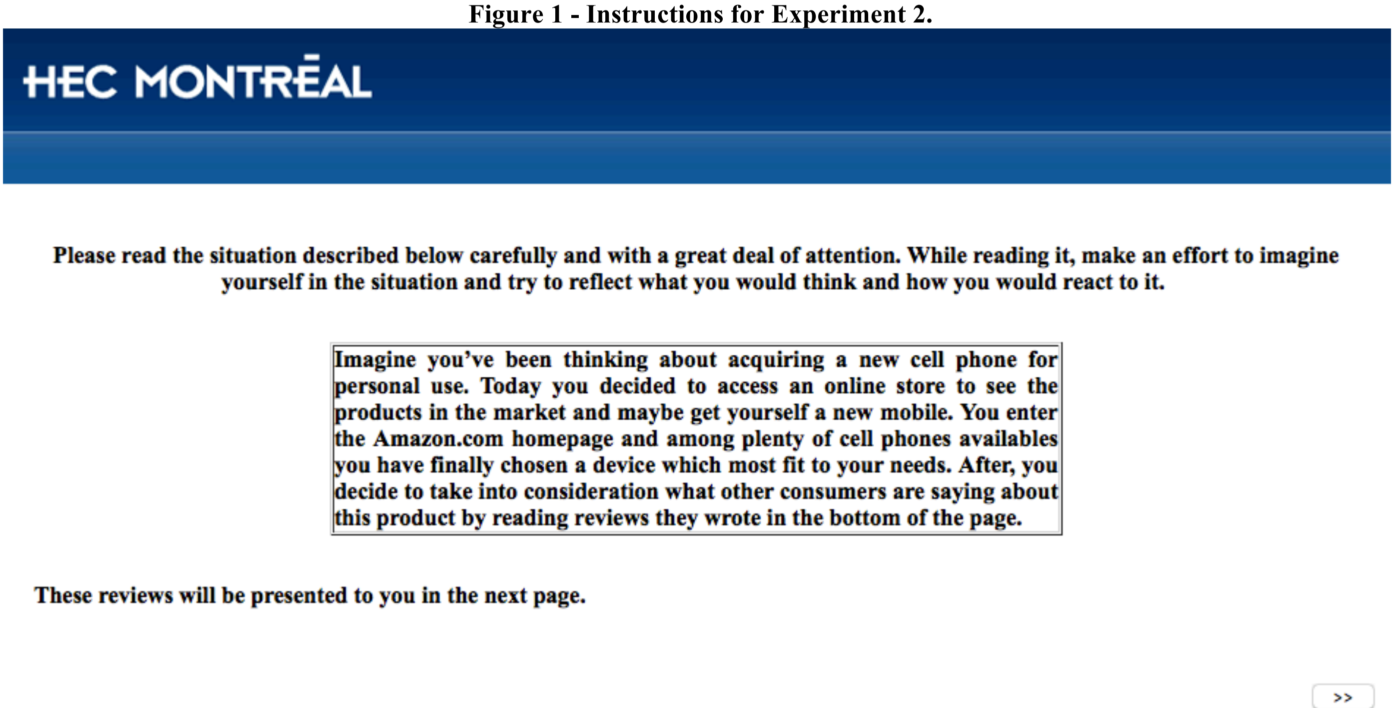
2.5.1.1 Design and Participants

A between-subjects single factor design (Evaluability: Textual, *T;* Graphic, *G;* and Both, *B*) was performed. As well as in the previous study, the variable was manipulated to reflect the definition of evaluability according to Lurie and Mason (2007), however few details in the procedure and stimulus were improved, as we show next. Data were collected through Qualtrics and Amazon Mechanical Turk (N = 106, 63 men; mean age = 34) with participants from the United States. As a prerequisite all participants should have at least 95% of approval in previous HITs and not having answered before the pre-test questionnaire neither the first experiment.

2.5.1.2 Procedures

In the first screen participants were told they were participating and collaborating with an academic research. Differently from the previous study, after the first screen participants were presented to the following message (Figure 1).

Figure 1 - Instructions for Experiment 2.

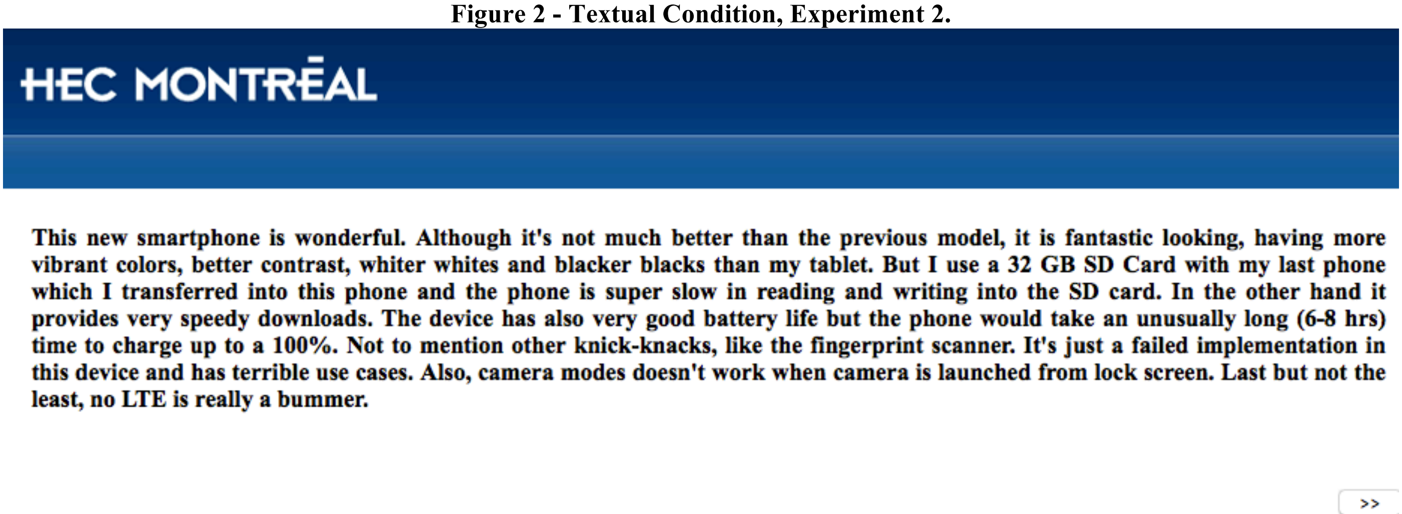


By clicking in the "next" button, participants were presented to one of the experimental conditions, which were composed only by the product's review, not mentioning neither the brand nor model and other characteristics that may affect the manipulation. After reading the review, participants were invented to answer a brief questionnaire containing the scales. Then, some demographics information was collected and the debriefing was held.

2.5.1.3 Stimulus

As stimulus it was used two real product (cell phone) reviews extracted from Amazon.com website as the most helpful review of that product, ranked by own customers (one with good evaluation and the other with poor evaluation about the product). In the “Textual” condition (Figure 2) six positive and six negative information (attributes) extracted from this review were presented to participants in a single paragraph text, randomizing the order of the attributes.

Figure 2 - Textual Condition, Experiment 2.



In the “Graphic” condition (Figure 3), the same attributes were presented but now in a table containing two columns, one for “positive attributes” and other for “negative attributes”. Differently from the previous study, in this experiment not only the attributes were presented, but also the whole phrase (i.e.: “Camera modes doesn't work when camera is launched from lock screen”). Again, the order of presentation of which column would be shown firstly was randomized.

Figure 3 - Graphic Condition, Experiment 2.

Pros	Cons
Wonderful phone	Not much better than the previous model
Fantastic looking	Phone is super slow in reading and writing into the SD card
Vibrant colors	Take an unusually long (6-8 hrs) time to charge up to a 100%
Better contrast	Fingerprint scanner is just a failed implementation
Whiter whites/blacker blacks	Fingerprint scanner has terrible use cases
Speedy downloads	Camera modes doesn't work when camera is launched from lock screen
Very good battery life	No LTE is really a bummer

In the last condition, “Both”, we have used again the same attributes but half of them presented in a text format (like in the *T* condition) and the other half in a table (like in the *G* condition) (Figure 4).

Figure 4 - Both Condition, Experiment 2.

The device has better contrast, whiter whites and blacker blacks than my tablet. The fingerprint scanner is just a failed implementation in this device and has terrible use cases. Also, camera mode doesn't work when camera is launched from lock screen. It provides very speedy downloads and has also very good battery life. Last but not the least, no LTE is really a bummer.

Pros	Cons
Wonderful phone	Not much better than the previous model
Fantastic looking	Phone is super slow in reading and writing into the SD card
Vibrant colors	Take an unusually long (6-8 hrs) time to charge up to a 100%

2.5.2 Results and Discussion

Besides testing again the relations previously presented, this study also aimed to analyze to what extent Involvement can moderate these relations. To measure Involvement, it was used a 5-item scale adapted from Mittal (1995) ($\alpha = 0.81$).

2.5.2.1 Helpfulness

A one-way ANCOVA was conducted considering Evaluability as independent factor, Helpfulness as dependent factor and Involvement as covariate. As in the previous study, to explore how helpful were the information presented to participants we used a scale from 1 to 5 (very unhelpful – very helpful, $\alpha = 0,82$).

Preliminary checks were conducted to ensure that there was no violation of the assumptions of normality, linearity, homogeneity of variances, homogeneity of regressions slopes, and reliable measurement of the covariate for the three outcomes presented in this study.

We observed a significant impact of the interaction between evaluability and involvement on helpfulness ($F (2, 103) = 7.32$, $p \leq 0.05$, $p\eta^2= 0.19$). To test this moderation effect it was used the Model 1 from PROCESS macro for SPSS (Hayes, 2013). The results are consistent with the ANCOVA results. Evaluability impacts on helpfulness ($p<0.05$) and Involvement does not impact on helpfulness ($p = 0,579$). However, the interaction between evaluability and involvement has a significant effect on helpfulness ($b = 0,39$, $se = 0,17$, $t = 2,29$, $p < 0.03$), proving that involvement moderates the relationship between evaluability and helpfulness.

2.5.2.2 Purchase Intention

A one-way ANCOVA considering Evaluability as independent factor, Purchase Intention as dependent factor and Involvement as covariate were performed. To explore how likely participants would purchase the cell phone after reading the reviews we used the same scale as in the previous study. We observed a significant impact of the interaction between evaluability and involvement on helpfulness ($F (2, 103) = 5.41$, $p \leq 0.05$, $p\eta^2= 0.15$).

To test this moderation effect it was used the Model 1 from PROCESS macro for SPSS (Hayes, 2013). The results are also consistent with the ANCOVA results. Evaluability impacts on purchase intention ($p<0.04$) and Involvement does not impact on purchase intention ($p=0.861$).

However, the interaction between evaluability and involvement has a significant effect on purchase intention (b = 0.57, se = 0,23, t = 2.48, $p < 0.03$), proving that involvement moderates the relationship between evaluability and purchase intention.

2.5.2.3 Overestimation of Information

A one-way ANCOVA was conducted considering Evaluability as independent factor, Overestimation of Information as dependent factor and Involvement as covariate. Participants were told to recall three attributes about the reviews. We, then, attributed weight to those recalls according to their valence ("+" for positive attributes and "–" for negative) ending up in a score, as in Study 1.

For the variable Overestimation of Information, the interactions between Evaluability and Involvement was not statistically significant ($F(2, 103) = 0.92$, $p = 0.351$, $p\eta^2 = 0.0197$), showing that involvement does not moderates the relationship between evaluability and overestimation of information. The analysis show, also, that involvement has no direct effect on overestimation of information ($F(1,148) = 2.52$, $p = 0.267$, $p\eta 2 = 0.0933$). Involvement has also no statistical significant correlation with overestimation of information, being excluded from the model.

However, as in Study 1, there is a main effect of evaluability on overestimation of information. We found significant difference in levels between groups ($F(2, 103) = 23.2$, $p \leq 0.05$, $p\eta^2 = 0.2$). Using Tukey HSD we found that the average of the *T* group (M = -6.08) was significantly different from the *B* group (M = -1.23). The G group (M = 3.09) was significantly different compared to the B group. Also, The *T* group was significantly different compared to the *G* group.

Briefly, we found in the study 2 important moderating effects of involvement in some of proposed outcomes. Involvement has a moderating role in the relation between evaluability and helpfulness as well as in the relation between evaluability and purchase intention.

2.6 Conclusions and Future Directions

This research presents some empirical, theoretical and managerial contributions. Empirically, analyzing the first experiment we found that different ways of presentation of the same online review can influence not only the purchase intention, but also how helpful consumers perceive that information to make a decision and how they overestimate one or other kind of information depending on the information presentation.

We can assume people exposed to the graphic review are too much disposed to buy the product than people exposed to the textual condition, and people presented to textual and graphic reviews consider the information more helpful than those presented to reviews containing both presentations. Also, consumers overestimate one or other kind of information depending on how this information is presented. Participants allocated in the *T* group recall much more negative information or attributes presented in the review than the *G* group, for example, which recalled more positives than negative attributes.

Regarding the second experiment, we found evaluability impacts on purchase intention and Involvement does not. However, the interaction between evaluability and involvement has a significant effect on purchase intention proposing involvement moderates the relationship between evaluability and purchase intention. We also observed a significant impact of the interaction between evaluability and involvement on helpfulness. Evaluability impacts on helpfulness but involvement does not. However, the interaction between evaluability and involvement has a significant effect on helpfulness proving that involvement moderates the relationship between evaluability and helpfulness. For the variable Overestimation of Information, the interactions between Evaluability and Involvement was not statistically significant showing that involvement does not moderates the relationship between evaluability and overestimation of information.

The theoretical contribution of this research is twofold. First, regarding the CFT and CLT, theories used as a background for this research. CFT say when a data format fits for its use (representation and task are matching), more effective and efficient problem-solving performance is achieved. We found similar results in this research, once when the information provided to costumers were presented in a graphic condition, we found better levels of helpfulness and overestimation of information.

However, when we presented the condition which both visual elements were presented (graphic and textual information) some of these measures were even better, which may led into what CLT poses when saying different kinds of information presentation, at the same time, reduces the cognitive load and leveraging performance. Second, through this research we could follow Lurie and Swaminathan (2009) suggestion in analyzing the potential moderating role of involvement may play because many visualization tools require consumer/user effort. We found that this moderating role, at least to date, occurs only for purchase intention and helpfulness when analyzing evaluability.

The managerial contribution of this research addresses mainly in the fact online retailers can take advantage of these findings when developing their web interfaces or e-commerce strategies. Slightly differences in the configuration of the online reviews section of the websites, like presenting the reviews using a textual or tabular layout, can bring important differences in terms of perception of the website from consumers and, also, increasing costumer's purchase intention.

Finally, as avenues for future research, we are intending to encompass the moderating role of expertise in these relations. It may led into different results once how much visual representations change cognitive processes likely depends on users' knowledge of which factors are important and the user's ability and motivation to change the visual representation to reflect these factors. At the same time, there is evidence that (novice) decision makers tend to use information as it is presented and that these decision makers often do not know which features are relevant for product evaluations (Slovic 1972; Sujan 1985).

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CHAPTER 3

Article 2: "The impact of depth-of-field and type of search on online consumer information search"

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3.1 Abstract

Online consumer information search became a crucial initial step in the purchase decision process. Using an experimental design in a real online store, this article analyze how depth-of-field and type of search may influence pre-purchase online seeking behavior, more specifically, the intention to revisit the website, the information acquisition after viewing the website and its information quality and visual appeal. We conducted a series of moderation analysis to broader the knowledge on involvement, attitude toward products and expertise as potential moderators to these relations. We also found statistically significant difference in means for intention to revisit, visual appeal, and information acquisition between the four experimental conditions in a 2x2 design. However, when analyzing separately each variable, we noticed only depth-of-field was responsible to produce such effects. The findings of this research may contribute to online store designers and e-commerce marketers in way to help understand how consumers behave while looking for product's information online.

Keywords: *E-commerce; Information visualization; Online information seeking behavior.*

3.2 Introduction

Today, it seems consumers are looking for information about products everywhere and one of the preferred places to make this kind of inference is the Internet, even if they are just browsing through some website or if they are really intending or decided to make an online purchase. According to a study carried by Google partnered with Ipsos MediaCT and Sterling Brands (2016), eighty-one percent of shoppers conduct online research before they make a purchase. Sixty percent begin by using a search engine to find the products they want, and 61 percent will read product reviews before making any purchase. The study also reveals that consumers want more information and customized experiences during their shopping journey, once two in three shoppers who tried to find information within a store say they didn't find what they needed, and 43% of them left frustrated.

On the one hand, even if consumers are just browsing a webpage or already decided to make a purchase they, each day, are facing an increasing amount of information online (Agrawal, Li, Berthouzoz, 2011) and this massive quantity of data may influence their behavior online. On the other hand, companies are facing a difficult trade-off on this phenomenon. While a huge amount of data on a product's webpage can help potential clients to make their decision it can, also, have the opposite effect, i.e., people could perceive this amount of data, even unconscious, as a barrier to make such decision.

Consumer information search has been the focus of numerous articles in the consumer behavior, economics, and marketing literature over the past three decades (Beatty and Smith 1987, Moorthy et al. 1997, Klein and Ford 2003). In recent decades, there have been many investigations into consumer search behavior in a digital environment (Chatterjee and Yawei 2010, Wu and Rangaswamy 2003, Alba and Hutchinson 1997) in the context of search attributes (Lynch and Ariely 2000, Klein 1998) and media interactivity (Alba and Hutchinson 1997, Klein 1998). It is worth noting that in digital environment consumer information pre-purchase and search behavior is different from traditional search behavior (Alba and Hutchinson 1997, Brynjolfsson and Smith 2000). Jansen and Pooch 2001 report that Internet searchers use different search characteristics to traditional seekers and the way information is presented can influence many individual’s behavior/perceptions during a webpage visit.

Information visualization techniques can work trying to resolve the problem of facing too much data during the pre-purchase online information seeking. By visually changing the way the same information is presented in a website, for instance, it is possible to influence consumers perceptions about a given webpage. For example, it’s known from several A/B testing experiments that changing the color of the “buy” button from green to red can increase the purchase conversion. This open avenue to study other kind of variables, besides color, that may influence consumer’s perceptions.

One of these variables is the depth-of-field, or the extent to which visual representations provide contextual overview versus detail information, according to Lurie and Mason (2007). This kind of variable can be perceived, for example, when people are in doubt between two or more products to buy online and they have the options to analyze both product’s attributes at once or if they need to open different tabs or pages to make this comparison. Although depth-of-field alone is likely to affect how information is accessed and evaluated (Ganapathy, Ranganathan, and Sankaranarayanan, 2004), in this article we also study the influence of the type of search consumers are involved, if just browsing in a webpage or if they have a goal-oriented task, i.e.: make a purchase decision.

Using an experimental design with a real online store, in this article we analyze how depth-of-field and type of search may influence pre-purchase online seeking behavior, more specifically, the intention to revisit the website, the information acquisition after viewing the website and its information quality and visual appeal. We also conducted a series of moderation analysis to broader the knowledge on involvement, attitude toward products and expertise as potential moderators to these relations.

We found statistically significant difference in means for intention to revisit, visual appeal, and information acquisition between the four experimental conditions in a 2x2 design. However, when analyzing separately each variable, we noticed only depth-of-field was responsible to produce such effects. The moderation analysis found different levels of involvement and attitude toward products influence our outcomes when manipulating webpage’s depth-of-field. The findings of this research may contribute to online store designers and e-commerce marketers in way to help understand how consumers behave while looking for product’s information online.

3.3 Literature Review

3.3.1 Growing data, Online search for information and the Visualization aid

The amount of information available to consumers is growing, and the rate at which people worldwide generate new data is growing exponentially annually. It is estimated that we are adding 2.5 quintillion bytes of data every single day (Siegel, 2013), and we are thus currently expected to produce ten times more data/year than the amount we used to produce ten years ago (Agrawala, Li, Berthouzoz, 2011).

However, when talking about marketplaces or e-marketplaces, Lurie (2004), Schwarts (2004) and many other authors, say the benefits of all this information are often unrealized because managers and consumers are increasingly overloaded with information, mainly in electronic environments. According to Sloman (1996), a solution for this information overload could be to present information using methods that engage the associative system, in which meaning is ascribed through gestalt and automatic processes, such as visual recognition, e.g.: the possibility to compare options in the same webpage.

Nowadays, consumer information search is a crucial component of the purchase decision process. This process is typically comprised of steps evolving from problem recognition, onto information search, before evaluating alternatives, in order to formulate a purchase decision (Bettman et al., 1991; Olshavsky, 1985; Schmidt & Spreng, 1996). Conventional sources, such as newspaper and magazine advertisements, radio and television commercials have been complemented during the last decade by information sources implemented using Internet technology. For many people, searching and comparison-shopping on the Internet is increasingly a daily behavior, once Internet has made enormous amounts of information available easily to consumers. While the total amount of information available to consumers increases the ability to absorb, it remains limited, leaving many consumers at a loss with regard to purchase decisions.

Search for information is frequently executed in relation to purchases (Klein and Ford 2003, Urbany, Dickson and Wilkie 1989, Öörni 2003), yet, consumers tend to limit the search to a handful of products and vendors (Öörni 2003), because search takes time and effort, and thus is costly.

Aligned with this, the study of consumer choice and decision processes has been an active topic in consumer behavior research for over fifty years (Howard and Sheth 1969, Bettman 1979). While pre-purchase search has received considerable academic attention during the decades it is still a high priority topic and recently even gaining in importance as increasing Internet penetration dramatically expands many markets and allows consumers to change their information search behavior.

In a general way, information search centers on obtaining information to aid decision-making amongst options in relation to a potential purchase. Using the economic approach to external information search, put forward most notably by Stigler (1961), a pre-purchase information search can be viewed in a cost benefit framework. Moorthy et al. (1997) suggest that the benefit of search to a consumer comes from what the authors refer to as “problem framing” as well as “involvement” and the consumer’s level of risk aversion. Ultimately, the pre-purchase information search should serve to reduce uncertainty amongst options so as to quell a consumer’s aversion to risk.

Therefore, one of the main objectives facing marketers is to present consumers with information on which to base their decisions (Anderson and Rubin 1986; Bettman 1975). Presenting such information is not simple, and it contains an interesting dilemma. On the one hand, a vast amount of information could be relevant to some consumers. On the other hand, presenting superfluous information might impede consumers’ ability to make good decisions.

Thus the task facing marketers is not simply to present consumers with every piece of semi-related information but, rather, to present consumers with information that is appropriate for their specific current needs. The difficulty is that marketers cannot always know a priori what information is needed for any individual consumer. Without knowing what information is relevant, the amount of information that is potentially relevant can be very large. In order to solve this difficulty, marketers can provide consumers with different ways to show information, allowing consumers to be appropriately selective in their own information search (Ariely, 2000).

Information visualization techniques can work trying to resolve the problem of facing too much data during the pre-purchase online information seeking. By visually changing the way the same information is presented in a website, for instance, it is possible to influence consumers perceptions about a given webpage. This open avenue to study other kinds of variables that may influence consumer’s perceptions.

The study of a better way to show some information through different visualization techniques, or information visualization as said before, is crucial to help companies deliver the most accurate information for consumers, in such a visual way that most fits consumer’s needs when searching for information online. Thus, it is no surprise that of the 11 million bits of information processed by the human brain per second, 10 million bits are dedicated to our visual system. The prominence of visually based decision making is particularly relevant in consumer choice, where the relative visual appeal of various offerings often determines preferences and decisions (Jia et al. 2014).

A key goal of much information visualization is to provide a compact representation of the information space to assist users/consumers in considering and navigating the space. The notion of overview has consequently been focal to information visualization research. Overviews of information spaces offer many benefits to the user. Many authors write about users gaining an overview of the information space, which we will refer to as overviewing. Spence (2007) noted that the term overview implies a qualitative awareness of one aspect of some data, preferably acquired rapidly and, even better, pre-attentively: that is, without cognitive effort (Hornbaek, Hertzum, 2011).

Moreover, individual context may cover the knowledge individuals' cognitive styles, personal preferences, and prior knowledge of relevant problem domains, skill acquisition abilities, age, and gender. These contextual factors are diverse and dynamic, which, in turn, may cause the huge complexity inherent in a knowledge visualization context. Therefore, the visualization requirements for solving the same decisional problem may vary when contextual changes occur. Context complexity can significantly affect the effectiveness of knowledge visualization regarding how well it can support a knowledge individual in solving the decisional problem of interest and achieve the intended purpose. The lack of concern regarding such an impact may incur issues with ineffective knowledge visualization design and visualization misuse (Bai, White, Sundaram; 2012).

3.3.2 Depth-of-Field

Lurie and Mason (2007) use the term "visual perspective" to refer to how a given visual representation changes the relation between visual information and the decision maker. The authors state that the first aspect of visual perspective is "interactivity," or the user's ability to change perspective, for example, by rotating or simulating movement around an image. The second aspect of visual perspective is "depth-of-field," which refers to whether a tool provides context by displaying an overview of large numbers of data points and/or more focused detail information on particular data points of interest.

Visual representations vary in depth of field, which is the extent to which visual representations provide contextual overview versus detail information or enable decision makers to maintain both levels in focus simultaneously (Lurie and Mason, 2007). Depth is likely to affect how information is accessed and evaluated (Ganapathy, Ranganathan, and Sankaranarayanan, 2004).

However, visualization tools that deliver more context rather than more detail, and tools that enable more alternatives to be displayed in a given visual field, may lead to relatively less compensatory (more selective) decision processes as decision makers eliminate alternatives from consideration (Payne 1976).

Lurie and Mason (2007) discuss other approaches to combining context and detail such as using: different windows to provide both overview and detailed views (Beard and Walker 1990); bifocal views, in which centrally located information is magnified and peripheral information is presented in a demagnified or bill-board format (Spence and Apperley 1982); and fish-eye views, which distort information such that focal information is larger and nonfocal information is smaller. Some results show faster navigation and data identification when an overview is provided. However, others have found that, although user satisfaction is higher, navigation may be slower because of the additional cognitive load of addressing simultaneous views (Hornbæk, Bederson, and Plaisant 2002).

Hornbæk and Frøkjær (2001) find that offering both overview and detailed views increases the general understanding of content, that detailed views only lead to superior speed in answering explicit requests and that fish-eye views increase reading speed. This suggests that whether combining context and detail is superior to either one alone depends on whether the goal is to maximize accuracy or minimize effort. In particular, visual representations that provide contextual information should lead to more consistent preferences than those that do not. However, such representations are likely to involve greater decision-making effort and time.

3.3.3 Type of Search

Nevertheless the type of consumer's search, or seeking activity, is not a visual element, it may influence consumer's perception of several components of the website. Two main types of online seeking activities can be identified: browsing and directed search. Browsing is a seeking activity that is associated with situations in which the consumer is uncertain about the information available and is unsure whether his shopping requirements can be met, hence seeking out information in an exploratory fashion (Detlor et al., 2003; Rowley, 2000). In the case of directed search, the consumer has fairly specific requirements (Rowley, 2000) and is actively seeking out information with the intent of making a decision (Detlor et al., 2003). In this sense, directed search is more goal-oriented than browsing activities.

The goal-orientation of a consumer performing an online seeking activity is important as it can point to the type of information processing employed. Chernev (2003a) postulated that consumers with clearer preferences are more probable to use an ideal attribute combination when evaluating alternatives. Here, the ideal attribute combination represents a combination of product characteristics that best represent the preferences of the consumer and hence indicative of information processing by alternative. In contrast, those without these clear preferences or ideal attribute combination to compare alternatives, are more probable to use attributes of various alternatives for comparison (Simonson & Tversky, 1992) indicating information processing by attribute. Essentially, it would seem that those with a clear goal in mind when searching are more likely to use alternative-based processing whereas those that do not seem to favor attribute-based processing. In addition, Detlor et al. (2003) remarked that consumers who were in a directed-search mode preferred detailed product information in terms of product specifications, although it is unclear if this indicates a preference for alternative-based processing.

Rowley (2000) suggested that consumers refine their strategies and information requirements as they consider information gathered throughout the search process. This refinement may cause a gradual shift from an exploratory browsing mode to a more focused directed search (Shim, Eastlick, Lotz, & Warrington, 2001). The viewpoint of phased information seeking activities seems analogous to heuristics (Bettman, 1979; Bettman et al., 1991) whereby one decision strategy is first used to eliminate alternatives and then another strategy adopted to compare the remaining options in the choice set. In a more recent study, Montgomery, Li, Srinivasan, and Liechty (2004) propose a model of web browsing that accounts for the two states of navigation, browsing and directed search. Their model acknowledges that a user may switch between these two information seeking activities many times during a visit to a website depending on the user's current goals or state of mind. The different behavior on switching from browsing to more goal-oriented activities is suggested by Shi et al. (2013) as next step when aligning e-commerce and visual techniques.

3.3.4 An overlook on the outcomes of this study

3.3.4.1 Intention to Revisit

The intention to revisit a website covers a broad domain. People may revisit a website for information acquisition, transaction making, or both. Different purposes of revisiting a website may expose people to different types of risks and require different levels of commitment in the decision-making. Although revisiting a website is not as definitive a behavior as making a transaction, it is a prerequisite for making a purchase, and the failure to intend to revisit the website almost precludes making a purchase.

It is an effective indicator of a behavioral response to the various characteristics of the website. For example, when deciding whether to revisit a website, consumers focus on those aspects most relevant to their immediate concern rather than engaging in an exhaustive processing of all potentially salient characteristics of the website again. Following this line of thinking, knowing the intention to revisit a particular website is important when aligning with the previous knowledge about which of the website's areas consumers pay more attention. If consumer's intention to revisit a website is high, when doing so they will probably focus, at a first glance, in those elements (Cyr, Head, Larios, 2010).

This variable is also intimately tied with loyalty, and ''understanding how or why a sense of loyalty develops in customers remains one of the crucial management issues of our day'' (van der Lan et al., 2004, p. 156). Online shoppers are more likely to revisit a website if they like its design and capabilities (Falk and Miller, 1992; Junglas and Watson, 2004; Madden et al., 2000; Venkatesh and Ramesh, 2006). Despite the apparent importance of developing loyal relationships with customers, there is limited academic research on the relative importance on individual elements of website design (Cyr, Head, Larios, 2010).

3.3.4.2 Information Acquisition

For Xia and Monroe (2005), the majority of the research on information acquisition assumes that consumers know what product they want, and the purpose of a search is to find the appropriate brand. Additionally, the research implicitly assumes that there have been no other information acquisition activities prior to the decision to purchase the product. Direct information is one way that consumers acquire information. However, people also acquire information through more casual information-acquisition activities such as viewing retail display windows or through incidental exposure to information such as clicking the wrong link online.

Although consumers may not actively seek specific information during such casual activities, their senses are operating, allowing information to be obtained. Moreover, consumers may use such information without intention and awareness in their subsequent purchase decisions. These more casual information acquisition activities are referred to as browsing. (Xia, Monroe, 2005).

3.3.4.3 Information Quality

Information quality (IQ) has become a critical concern of organizations and an active area of business research. The growth of data and the direct access of information from various sources by managers and information users, like consumers, have increased the need for, and awareness of, high-quality information in organizations (Lee et al. 2002). Over the last decade, IQ research activities have increased significantly to meet the needs of organizations and individuals attempting to measure and improve the quality of information.

Ensuring quality of information produced, processed and consumed happens to be a major challenge and requires an efficient management of IQ. Research to develop the theme have been presenting broader views of the concept of IQ as Strong, Lee and Wang (1997) who claim that a high IQ can be attributed to information that suits the needs of those who consume. A similar view is provided by Kahn, Strong and Wang (2002), which define quality as the ability of a product successfully serve the purpose of those who consume it, eventually transplant the concept to the field of information.

Redman (2005) also has a similar view, however, reduces the semantic encompassing concept stating that the information can be considered of high quality when it is appropriate to its use by customers, operations, decision-making and planning. In turn, McGee and Prusak (1994) argue that IQ is achieved through a comprehensive care to the completeness, accuracy, timeliness, interpretability and general information value, judged by their customers.

To measure Information Quality in this work we use part of the WebQual instrument that has been under development since the early part of 1998 and has evolved via a process of iterative refinement in different e-commerce and e-government domains. Previous applications of WebQual include UK business school Web sites (Barnes and Vidgen 2000), Internet bookshops (Barnes and Vidgen 2001a), small companies (Barnes and Vidgen 2001b), and online auction houses (Barnes and

Vidgen 2001c). The method turns qualitative customer assessments into quantitative metrics that are useful for management decision-making.

3.3.4.4 Visual Appeal

The importance of visual appeal for consumers is recognized by both marketers and retailers, who constantly bombard consumers with more visual impressions through phalanxes of posters, picture-laden websites, and strategically arranged product displays (Jia et al., 2014).

Individuals form impressions of the visual appeal of websites in a fraction of a second. Lindgaard et al (2006) found that participants in their studies could form reliable impressions of a website's visual appeal in as little as 50 milliseconds, taking 250 milliseconds to blink. The researchers also found participants' ratings of the same 100 homepages were consistent over time. That is, if users think a webpage has low attractiveness at one point in time, they feel the same way at a future point.

Recently, an experiment was conducted wherein the researchers manipulated both the usability and visual appeal of an online ecommerce website (Tuch et al., 2012). The researchers essentially used one website, made the navigation intuitive or not intuitive, and changed the colors and contrast to be appealing or unattractive. Researchers found, somewhat to their surprise, that it was not the more attractive website that increased usability scores; on the contrary, it was the more usable websites that tended to increase measures of beauty. In short, the researchers did not find that what has great appeal is usable, but rather that what is usable has great appeal; this is an important causation difference from earlier studies that found correlations between measures of beauty and usability.

3.3.5 Individual Characteristics – Moderators

3.3.5.1 Expertise

How much visual representations change decision-making processes likely depends on users'/consumers' knowledge of which factors are important and the user's ability and motivation to change the visual representation to reflect these factors. At the same time, there is evidence that (novice) decision makers tend to use information as it is presented and that these decision makers often do not know which features are relevant for product evaluations (Slovic 1972; Sujan 1985).

Thus, when novice decision makers are presented with a particular visualization, they may assume that the variables represented are the most relevant and that the default visualization is best. This means that novice users may fail to take advantage of interactivity and will tend to use the default visualization, regardless of its appropriateness for a given task. For example, consumers may be less likely to recognize improvements in reliability for a particular brand if the default view is a scatter plot rather than a sorted table visualization because scatter-plot views can make trends more difficult to observe (Kobsa 2001).

3.3.5.2 Involvement

For Lurie and Swaminathan (2009), involvement may play a moderating role because many visualization tools require user effort. Using interactive visual representations to restructure information and explore different options requires the decision maker to identify which aspects are important and interact with the visualization to display these aspects. Similarly, using visualizations that involve selecting or eliminating alternatives requires the decision maker to play an active role. Unless the decision is sufficiently important, the user may be unwilling to engage in the cognitive and physical effort needed to realize the full benefits.

3.3.5.3 Attitude toward product

As in Mathwick & Rigdon (2004), the concept of Involvement is intimately linked with the attitude consumers have to the focal product in the website. Whether discussing the shopping experience in general or the information search experience specifically, this literature suggests that the experience matters. Its influence is imprinted on value perceptions, attitudes, and loyalty outcomes. Therefore, when online information search creates value, that positive experience is hypothesized to transfer to attitudes toward the product, as well as toward focal website, firm and its brands.

3.4 Experiment

3.4.1 Method

3.4.1.1 Participants

Data were collected through Qualtrics with Amazon Mechanical Turk workers (N = 140, 61 men; mean age = 31) with participants from the United States. As a prerequisite all participants should have at least 95% of approval in previous HITs and not having answered before the pre-test questionnaire.

3.4.1.2 Design and Stimuli

A between-subjects design 2 (Depth-of-Field: Products presented by Attribute, *AT;* Products presented by Alternative, *AL*) X 2 (Type of Search: Goal Oriented, *GO;* Browsing, *BR)* was performed. The study was operationalized and collected through Qualtrics software. The first screen of the questionnaire provided clarification and a generic objective of the study.

To make the participants experience in an online retail environment appear real, scenarios were presented using a webpage from a leading computer/notebook store in the e-commerce segment in US/Canada in partnership with the laboratory where research was conducted. The first variable (Depth of Field) was manipulated by changing how the information of a product was presented, if showing information by alternative or attributes (see Figures 5 and 6).

Figure 5 - Products by Attribute

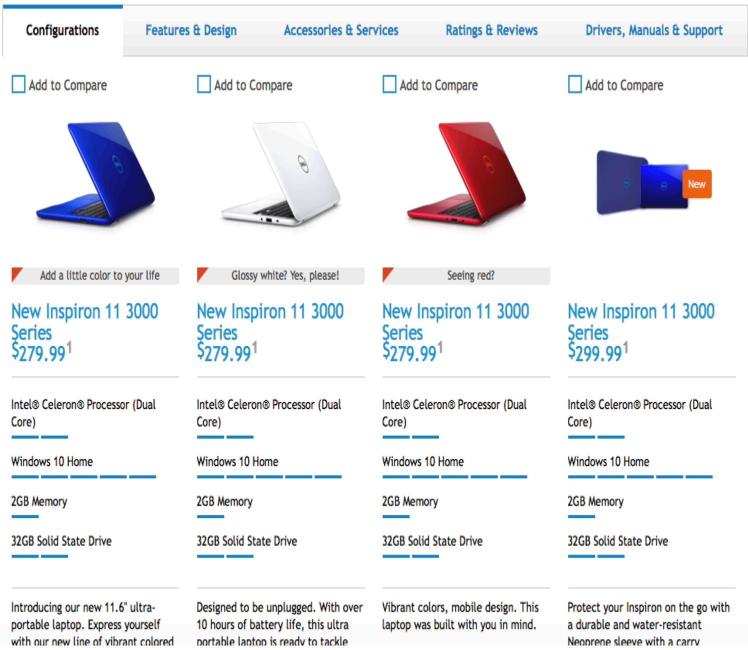
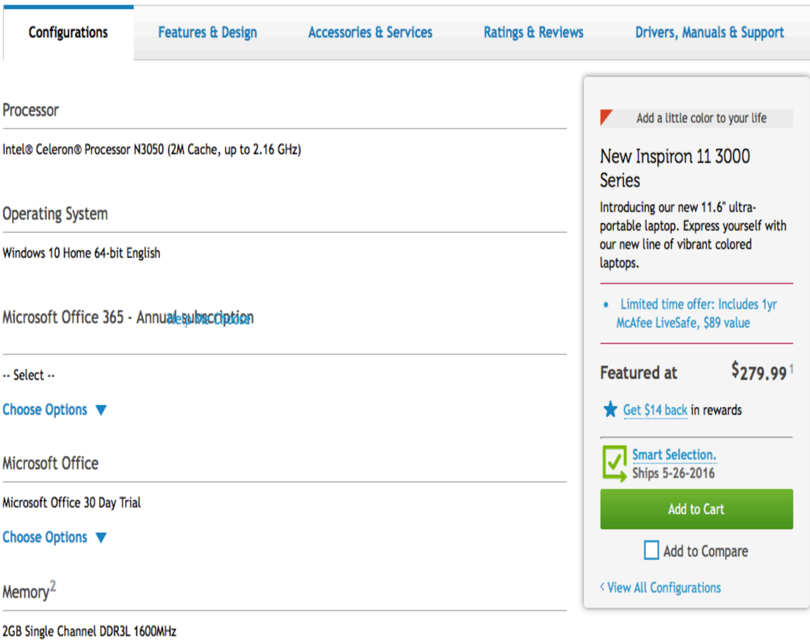


Figure 6 - Products by Alternative



The second independent variable was manipulated in the text presented to subject before he/she accessed each of the four webpages. The instruction varied accordingly to manipulations, to reflect a browsing situation ("Imagine you are navigating on the web and accessing the following webpage…") and a purchase task ("Now you have to buy a personal computer for yourself …").

3.4.1.3 Procedure

Data collection was realized during the second semester of 2015. Participants were exposed to four different conditions assigned randomly between subjects. Subjects were asked to participate in an academic research and to follow the instructions on the screen. After visualizing the webpage, participants answered a questionnaire containing some behavioral measures (see below). After the interaction with the webpage, participants responded to measures of the dependent variables. Thereafter, demographic, realism of the scenario and manipulation check questions were collected. Finally, the debriefing was held and participants received the code for monetary compensation ($ .35 each).

3.4.1.4 Measures

3.4.1.4.1 Dependent Variables

Many variables were considered in this study. It was expected direct effects of the treatments on (1) Intention to Revisit, (2) Information Acquisition, (3) Information Quality, and (4) Visual Appeal. All variables were measured by scales used in other studies and established in the literature as follows.

Intention to Revisit was measured in accordance with Netemeyer et al. (2004), asking participants, after the stimulus presentation, “How likely would you revisit this webpage?” using a 5-point scale (very unlikely – very likely).

Information Acquisition was measured by a modified scale (α = .812) from Murray (1991) study. Participants rated on a seven-point scale (totally disagree – totally agree) the following statements: a) “I paid attention to what previous costumers said about the product in this page”; b) “I am ready to make a purchase selection and not worried about acquiring more information prior to buying”; c) “I have much more information about the product after visiting this page”; d) “I was able to see different kinds of information provided by the seller”; e) “ I tried to recall relevant events which I can associate with this product or service”.

Information Quality scale used in this article is part of WebQual 4.0 Scale, from Barnes and Vidgen (2002) (α = .778) Participants rated on a eight-point scale (disagree –agree) the following statements: The webpage I’ve seen… a) “has sufficient contents where I expect to find information”; b) “provides complete information”; c) “provides site-specific information”; d) “provides accurate information”; e) “provides timely information”; f) “provides reliable information”; and, g) “communicates information in an appropriate format”.

Additionally, Visual Appeal was measured using a scale from the Lindgaard et al. (2006) study (α = .907). In this scale, the following items generate the most reliable and valid measure of "visual appeal." Participants rated these on a nine-point scale: a) interesting –boring; b) good use of color – bad use of color; c) well designed – poorly designed; d) good layout – bad layout; and, e) imaginative – unimaginative. A combination of these five items predicted, according to Lindgaard et al. (2006), 94% of visual appeal ratings for website homepages.

3.4.1.4.2 Moderator Variables

As mentioned earlier, some variables were controlled to evaluate to what extent they impact in the study's results. Therefore, the control variables are included in the analysis model (treated as covariates in the analysis of covariance), and their control effects on the dependent variables will be identified.

Thus, Expertise of the subject in relation to Internet purchase, participant's attitude towards product and the participant's level of Involvement while performing the task were controlled. These measurements were made at the end of procedures.

To determine participants' level of involvement or engagement with the task, we inquired, in accordance with Karmarkar and Tormala (2010), two questions adapted from past research (e.g., Petty and Cacioppo 1979): "How involved did you feel with the task?" and "How interested were you in the task?" Responses were provided on scales ranging from 1 (not involved at all, not interested at all) to 9 (very involved, very interested). (Karmarkar and Tormala, 2010).

The measure for individual's attitude towards product were extracted from Mathwick & Rigdon (2004) asking parcitipants "What do you think about the presented product" using a 3-item seven-point scale (Good-Bad; High quality-Low quality; Dislike very much-Like very much).

Additionally, participants answered a scale, adapted from Clarkson, Janiszevswki, Cinelli (2013), regarding their expertise in relation to internet purchasing. Embedded within this questionnaire were the subjective and the objective expertise items for the task. For subjective expertise, participants used 9-point scales to indicate their expertise ("not much expertise at all" – "a lot of expertise"), information ("not much information at all" – "a lot of information"), and understanding ("not much understanding at all" – "a lot of understanding") regarding the task. For objective expertise, participants used 9-point scales to indicate how often they buy on Internet ("not often at all" – "very often"), and how often they use Internet ("rarely" – "frequently"). The ordering of the expertise measures was randomized.

3.4.2 Results and Discussion

3.4.2.1 Preliminary Results

When comparing means from the four conditions of our experiment we found a significant effect for Intention to Revisit ($F(3, 136) = 21.03$, $p < .001$), Information Acquisition ($F(3,136) = 6.94$, $p < .001$) and Visual Appeal ($F(3,136) = 11.67$, $p < .001$). However, we did not find a significant effect on Information Quality ($F(3,136) = 1.26$, *ns*).

Intention to Revisit. Using Tukey HSD test we found the average of the B_ALT group (M = 3.26, SD = 1.01) was significantly different from the B_ATT group (M = 4.48, SD = .74) and GO_ATT group (M = 4.68, SD = 1.02), both at $p < 0.001$ levels. We also found the GO_ALT group (M = 3.34, SD = 1.02) group means were significantly different from those of the B_ATT and GO_ATT at $p < 0.001$ levels.

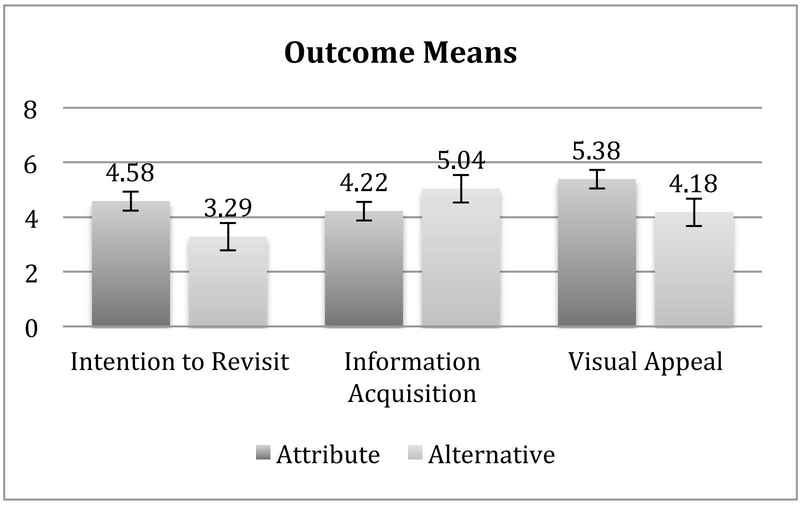
Information Acquisition. The results for this outcome reports the average of the B_ALT group (M = 5.22, SD = 1.21) was significantly different from those of the B_ATT group (M = 4.21, SD = .92) and GO_ATT (M = 4.19, SD = 1.11), both at $p < 0.002$ levels.

Visual Appeal. Also using Tukey HSD test we found statistically significant difference in means for B_ALT group (M = 4.25, SD = 1.5) when comparing to B_ATT group (M = 5.53, SD = 1.15, $p < 0.001$) and GO_ATT (M = 5.30, SD = .98, $p = 0.004$). Also, GO_ALT group (M = 4.07, SD = 1.39) differed statistically from B_ATT and GO_ATT groups, both at $p < 0.001$ levels.

3.4.2.2 The relative roles of Depth-of-Field and Type of Search on Outcomes

Was the effect on these 3 outcomes due to depth-of-field manipulation, type of search, or both? A 2 (Depth-of-Field) x 2 (Type of Search) ANOVA showed a significant main effect only for Depth-of-Field on Intention to Revisit $F(1, 138) = 63.78$, $p < .001$), Information Acquisition ($F(1,138) = 23.21$, $p < .001$), and Visual Appeal ($F(1,138) = 30.31$, $p < .001$). The effect of Type of Search was not significant for Intention to Revisit ($F(1, 138) = .54$, *ns*), Information Acquisition ($F(1,138) = .788$, *ns*) and Visual Appeal ($F(1,138) = .732$, *ns*). These results suggest that the significant differences in means for Intention to Revisit, Information Acquisition and Visual Appeal were induced by Depth-of-Field, rather than by Type of Search manipulations. Figure 7 presents the difference in means for participants grouped accordingly with the depth-of-field variable manipulation.

Figure 7 - Difference in means for participants accordingly to variable manipulation



(Error bars indicate ±1 standard error of the mean.)

Following the procedure as described in Reb and Connolly (2007) when grouped into two different categories (those who viewed information by Attribute or by Alternative), we found statistically significant difference in means for Intention to Revisit (diff. = 1.29, $p < 0.003$), Information Acquisition (diff. = .82, $p < 0.04$) and Visual Appeal (diff. = 1.2, $p < 0.002$).

3.4.2.2 The moderating roles of Involvement, Attitude toward Product and Expertise on Depth-of-Field

We next examined the possible moderating role of Involvement, Attitude toward Product and Expertise in linking Depth-of-Field with our outcomes. Table 1 summarizes the results. We only found significant moderation effects for Involvement and Attitude toward Product for the relation between Depth-of-Field and Intention to Revisit.

Table 1 - Summary of results of the influence of the moderating variables via ANCOVA

		Covariates		
Dependent Variables	IV	Involvement	Attitude toward Product	Expertise
Intention to Revisit	S	S	S	NS
Information Acquisition	S	NS	NS	NS
Information Quality	NS	NS	NS	NS
Visual Appeal	S	NS	NS	NS

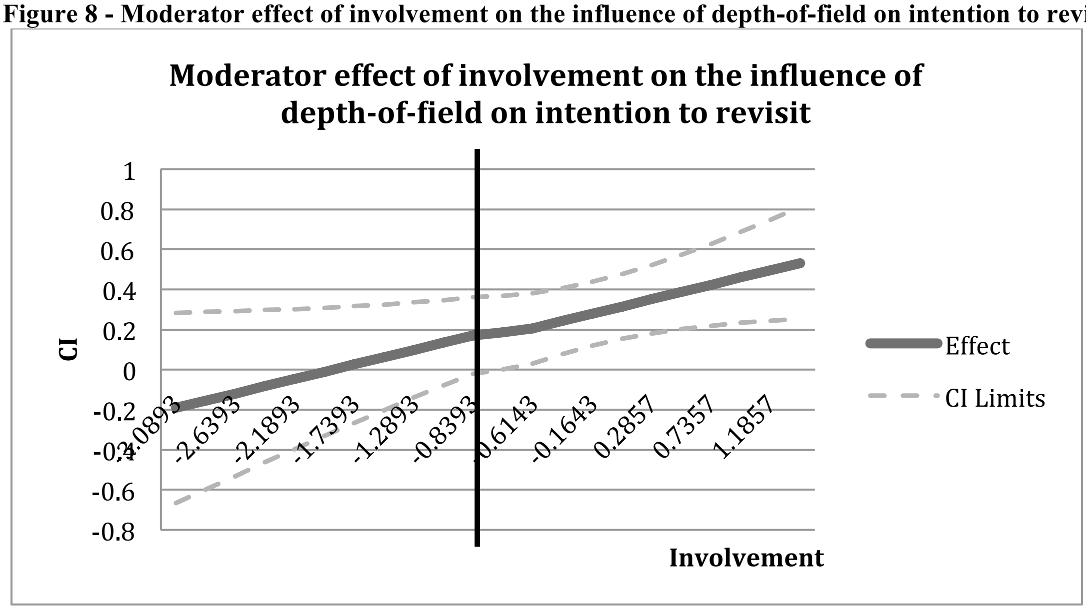
Note: S = significant; NS = non-significant effect; IV = independent variables
Source: Research Data

The moderation analysis was ran by Model 1 from PROCESS macro for SPSS by Hayes (2013), which considers the impact of an independent variable X on a dependent variable Y and a moderation of a M variable. The bootstrap sample size was 5000 as recommended by Hayes (2013). The method for confidence interval generation via bootstrapping was the bias corrected, and the Johnson-Neyman test was performed to identify in what point of the moderator variable the independent variable impacts on the outcomes.

The analysis was held considering depth-of-field as independent factor, Intention to Revisit, Information Acquisition and Visual Appeal as dependent factors and Involvement, Attitude toward Product and Expertise as covariates. Preliminary checks were conducted to ensure that there was no violation of the assumptions of normality, linearity, homogeneity of variances, homogeneity of regressions slopes, and reliable measurement of the covariates for the three variables.

Depth-of-Field directly influences the intention to revisit ($b = .3052$, $se = .081$, $t = 3.77$, $p = .002$, CI: .1453-.4650). Involvement does not influence directly on the Intention to Revisit ($b = .068$, $se = .077$, $t = .879$, $p = .381$, CI: -.085-.221), as well as Attitude toward Product does not ($b = -.297$, $se = .0963$, $t = -3.09$, $p = .24$, CI: -.488-.147) However, the interaction between depth-of-field and involvement has a statistically significant impact on the intention to revisit ($b = .1609$, $se = .076$, $t = 2.11$, $p = .036$, CI: .0105-.3113), the same way as Attitude toward Product does ($b = -.1689$, $se = .0856$, $t = -1.973$, $p = .05$, CI: -.3382-.0004). Figures 8 and 9 explicit how these moderators influence these relations.

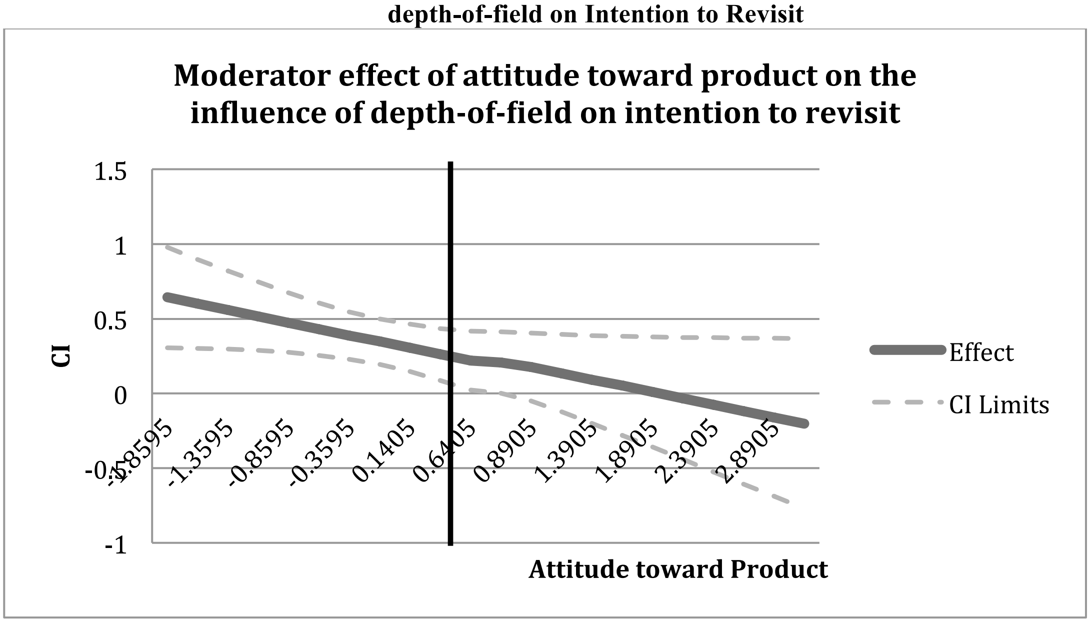
Figure 8 - Moderator effect of involvement on the influence of depth-of-field on intention to revisit



Obs.: Values on the right-hand side of the vertical plotted line are significant at $p < .05$ levels.

Figure 8 shows, as involvement levels gets higher, the effect of the interactions between depth-of-field and intention to revisit gets stronger until achieve a statistically significance. Specifically, Figure 8 shows the effect of involvement on the intention to revisit and its confidence intervals (CI) (y axis). This effect starts to become statistically significant at -.75 levels of the involvement variable (vertical line plotted in the graph, or the exact moment when the effect starts to become significant). On the left-hand side of this line, we found p values ≥ 0.05, while in the right-hand side we found p values lower than 0.05. So, for people with an involvement level lower than this point the effect is not statistically significant, while for people having an involvement level higher than this point involvement increases the intention to revisit the website.

Figure 9 - Moderator effect of Attitude toward Product on the influence of depth-of-field on Intention to Revisit



Obs.: Values on the left-hand side of the vertical plotted line are significant at $p < .05$ levels.

Figure 9 shows, as attitude toward products levels gets higher, the effect of the interactions between depth-of-field and intention to revisit gets weakened until achieve a point where it is not statistically significant anymore. Specifically, Figure 9 shows the effect of attitude toward products on the intention to revisit and its confidence intervals (CI) (y axis). This effect starts to become statistically insignificant at .72 levels of the attitude toward product variable (vertical line plotted in the graph, or the exact moment when the effect starts to become insignificant). On the left-hand side of this line, we found p values < 0.05, while in the right-hand side we found p values higher or equal 0.05. So, for people with an attitude toward product level lower than this point the effect is statistically significant, which means as lower as the attitude toward products gets, higher will be the intention to revisit the website, while for people having a level higher than this point attitude toward products is not significant.

3.5 Discussion, Managerial Implications and Future Directions

This research presents some empirical, theoretical and managerial contributions. Empirically, analyzing the experiment we found that different ways of presentation of the product online can influence outcomes such as the intention to revisit the website, websites' visual appeal and individual information acquisition.

From a theoretical perspective, we can assume people exposed to conditions where products were presented by attribute have a higher intention to revisit the website, as well as have a higher perception of the websites' visual appeal. However, this relation is the opposite when analyzing the individual information acquisition while visiting the website, once people exposed to the conditions where products were presented by alternative had higher scores for this variable.

It is important noting that when performing a 2 (depth-of-field) x 2 (type of search) ANOVA we found a significant main effect only for depth-of-field on intention to revisit, information acquisition, and visual appeal. The effect of type of search was not significant for intention to revisit, information acquisition and visual appeal and there was no evidence of a significant interaction. These results suggest that the significant differences in means for intention to revisit, information acquisition and visual appeal were induced by depth-of-field, rather than by type of search manipulations. This result goes against those presented by Chernev (2003) that found differences in type of search, however, it must be said that context studied by the author was an offline context, in opposition to the online used in this article.

We also examined the possible moderating role of involvement, attitude toward product and expertise in linking de depth-of-field with our outcomes. We only found significant moderation effects for involvement and attitude toward product for the relation between depth-of-field and intention to revisit. This corroborates the suggestion made by Lurie and Swaminathan (2009), as well as Mathwick & Rigdon (2004), to use those variables as potential moderators when evaluating differences in products visualization. Kobsa (2001), however, suggested the use of expertise as possible moderator in this context, but in this study we did not find a relation concerning this variable. This is probably due to the fact the experiment was carried using an online platform and, mainly, because almost all respondents have the same levels of experience shopping online.

Concerning the results of the moderation analysis, depth-of-field directly influences the intention to revisit and involvement and attitude toward products does not influence directly on this outcome. However, the interaction between depth-of-field and involvement has a statistically significant impact on the intention to revisit, the same way as attitude toward product does. We also found participants with a higher level of involvement (and as high it gets) have higher intention to revisit the website, while for participants with a lower level of attitude toward product (and as low it gets), higher will be the intention to revisit the website, expanding the findings from Lurie and Swaminathan (2009).

The managerial contribution of this research addresses mainly in the fact that online retailers and web designers can take advantage of these findings when developing their web interfaces or e-commerce strategies. Differences in the configuration of the product's presentation in the websites, like presenting them side-by-side facilitating attribute comparison, can bring important differences in terms of perception of the website from consumers and, also, increasing costumer's intention to revisit the website.

Finally, as avenues for future research, we are intending to analyze in further studies the in-shopping online information seeking, it means, how is the information seeking activities in a mobile device while consumers are shopping in a non-electronic store. It could also be expanded to see if there is difference if people are browsing through the website of the same store they are physically in or if they are browsing this information in an online store that is not the same they are in. Price and characteristics of the products may vary on physical and online retailers, and this information of how people deal with seeking activities may help managers better create and analyze their retailing strategies.

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CHAPTER 4

Article 3: "The Influence of Depth of Field and Type of Search on Pre-Purchase Online Information Seeking: An Eye-Tracking Analysis"

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(Working Paper)

4.1 Abstract

One of the main objectives facing marketers is to present consumers with information on which to base their decisions. In doing so, marketers have to select the type of information they want to use in order to deliver the most appropriate information to their consumers. Using an experimental design in a real online store, the first study of this article examines how depth-of-field and type of search may influence pre-purchase online seeking behavior, more specifically, the intention to revisit the website, the information acquisition after viewing the website and its information quality and visual appeal. The second study, used the same design of study 1, however, different outcomes were collected using eye-tracking analysis. The findings of this research may contribute to online store designers and e-commerce marketers in way to help understand how consumers behave while looking for product's information online.

Keywords*: E-commerce; Eye-tracking; Attention; Data Visualization.*

4.2 Introduction

Websites represent the most important form of interactive relations with clients, which is one of the fastest growing media today, according to Gartner (2016). As Internet usage is increasing worldwide, the focus of today's marketers is shifting from establishing a presence to strategic aspects related to products and to create effective communications tools with customers. This evolution, indeed, has broadened the horizon of where people can search for information about a product online.

Related to this, consumer information search is an important initial step in the purchase decision process. When consumers are faced with a purchase problem, information search allows them to gather information necessary to evaluate the alternatives, so as to make a final purchasing decision (Bettman, Johnson, & Payne, 1991; Schmidt & Spreng, 1996). In this regard, online information search comprises two types of searching activity being either browsing or directed search (Rowley, 2000). Browsing is a type of information search that is elicited when users are uncertain how their shopping needs can be satisfied and do not have a precise idea of what is desired. On the other hand, directed search (or goal-oriented) consists of seeking out specific information regarding a product, with the intent of making a purchase decision (Detlor, Sproule, & Gupta, 2003).

The type of information processing used is a characteristic of the various decision strategies, and this can be either by alternative or by attribute (Bettman, 1979). This idea was complemented by Lurie & Mason (2009) when they say these types of information processing can be presented in such a way that modifies the depth-of-field of a visualization. For instance, in alternative-based information processing, the focus is on a single alternative, acquiring information across multiple attributes for the alternative. Conversely, in attribute-based information processing, the focus is on obtaining information on a single attribute across various alternatives. Here, the major determinants of task complexity are said to be the number of alternatives as well as the number of attributes per alternative (Bettman, Johnson, & Payne, 1990; Payne, 1976).

It is important to note that certain characteristics of the online context can affect information seeking activities. Consumer's involvement on the task can impose some variations on outcomes, as well as their expertise regarding the "e-context" (Schmutz, Heinz, Métrailler, & Opwis, 2009), which may affect the way in which they seek out information on that particular site.

Some of the studies pertaining to the decision-making process described above investigate the two information-processing types in relation to decision strategies. Some studies have investigated the possible links between the aforementioned search activities (browsing and directed search) and information processing, but do so in an offline context, referring to search activities and choice selection in function of predetermined preferences (Chernev, 2003b; Simonson & Tversky, 1992).

The online context offers an immense availability of information and as users have limited information processing capacity (Bettman, 1979), the amount and type of information seeking activities may affect the attention processes towards the website. However, it is unclear in the literature whether online information search activities described above and the type of information presentation employed by e-retailers can indeed change some behavioral (i.e.: purchase intention, intention to revisit, etc.) and biological outcomes (i.e.: gaze and saccadic movements) when consumers are engaged in online pre-purchase information search.

Although a number of conceptual and empirical studies have focused on the importance of attention on certain elements of a website, we still do not have a good understanding of the processes of navigating websites, consumer responses to websites characteristics, or about the persuasiveness of this communication medium. This emphasizes the importance of developing and testing systematic models of the web as a tool, which would allow researchers and marketers to achieve a higher level of understanding.

This study seeks to contribute to online information seeking literature by investigating participant's online search and browse behaviors and the resulting processing of information when visualizing a product's webpage when visual information about the product is manipulated to reflect different levels of depth-of-field.

In view of these observed gaps, the objectives of the present article are three-fold: a) better understand the relation between depth-of-field and type of search on the information seeking behavior, b) providing a broader, more comprehensive study on web navigation behavior, integrating website navigational characteristics, consumer responses, and outcomes (biological and behavioral); c) offering companies the key visual elements where individuals pay more attention during a visit to a product's webpage. To achieve these objectives, the first experiment examines the influence of type of search and depth-of-field in the consumer online information seeking behavior using behavioral measures, while in the second experiment we expand those findings by including some biological outcomes from an eye-tracking experience.

4.3 Conceptual Background

It is known that online information search allows consumers to discover options available to them for a particular problem. In order to choose amongst options, consumers employ a variety of decision strategies and heuristics to narrow the number of choices so as to make a final decision on a particular option, especially when huge amount of data is presented. There are numerous decision strategies that can be employed and these vary from one consumer to the next. For example, one consumer may attend only to the specification of a product while another one may fix most of the attention on other consumer's reviews and ratings about the product.

Although it is difficult for an external observer to discern which of these decision strategies are being used by a consumer, it is possible to present information to costumers in such way that facilitates one or other type of decision making process, i.e.: presenting information by attribute or by alternative. The following sections aim to provide a common background on some ways to manipulate the information presented in an online retailer such as Amazon.com, Dell.com, etc., describing previous research on information visualization, different types of search and depth-of-field.

4.3.1 Information Visualization

Behind the saying that "a picture is said to be worth a thousand words" lies the recognition that daily decisions are heavily dependent on visual information. Thus, it is no surprise that of the 11 million bits of information processed by the human brain per second, 10 million bits are dedicated to our visual system. The prominence of visually based decision making is particularly relevant in consumer choice, where the relative visual appeal of various offerings often determines preferences and decisions (Jia et al. 2014).

One of the main objectives facing marketers is to present consumers with information on which to base their decisions (Anderson and Rubin 1986; Bettman 1975). Presenting such information is not simple, and it contains an interesting dilemma. On the one hand, a vast amount of information could be relevant, even very relevant, to some consumers. On the other hand, presenting superfluous information might impede consumers' ability to make good decisions (Bettman, Johnson, and Payne 1991; Jacoby, Speller, and Berning 1974; Malhotra 1982; Scammon 1977).

Therefore the task facing marketers is not simply to present consumers with every piece of semi-related information but, rather, to present consumers with information that is appropriate for their specific current needs. The difficulty is that marketers cannot always know a priori what information is needed for any individual consumer. Without knowing what information is relevant, the amount of information that is potentially relevant can be very large. In order to solve this difficulty, marketers can provide consumers with interactive information systems that allow consumers to be appropriately selective in their own information search (Ariely, 2000).

For Ziemkiewicz *et al.* (2012), visualization theory research has focused primarily on how to map data to visual forms and how people perceive these forms. Perceptual visualization theory attempts to understand and model how users perform fundamental low-level tasks. However, as visualization gains widespread importance, researchers are studying more complex tasks. Visualizations are now serving as cognitive aids in problem solving, as users begin relying on visualizations to help them solve increasingly difficult problems.

Moreover, individual context may cover the knowledge individuals' cognitive styles, personal preferences, and prior knowledge of relevant problem domains, skill acquisition abilities, age, and gender. These contextual factors are diverse and dynamic, which, in turn, may cause the huge complexity inherent in a knowledge visualization context. Therefore, the visualization requirements for solving the same decisional problem may vary when contextual changes occur. Context complexity can significantly affect the effectiveness of knowledge visualization regarding how well it can support a knowledge individual in solving the decisional problem of interest and achieve the intended purpose. The lack of concern regarding such an impact may incur issues with ineffective knowledge visualization design and visualization misuse (Bai, White, Sundaram; 2012).

For Ziemkiewicz et al. (2012), designing each visualization for an individual user would be impractical. However, knowledge of broad differences between user groups could help guide design for specific domains and help suggest multiple analysis modes or customization options in a single system. Recently, a promising research area has emerged that takes an opposing approach to a traditional "one size fits all" design. This suggests that the individual users' cognitive style, as much as the visual design, determines the visualization's value. Color and perceptual theories remain necessary to make good design decisions but alone, are insufficient to guide the visualization design for a cognitively complex task.

Although these findings are at an early stage, they suggest that we should not study visualization in a vacuum but in the context of differences among users. This, in turn, could lead to a shift in how we evaluate and design visualizations for different user groups, tasks, and domains. For this to happen, we must first understand what individual factors (that is, cognitive and personality factors) affect visualization use (Ziemkiewicz *et al.* 2012).

Because of the inherent dynamic nature, these contextual factors may cause the changing visualization requirements and difficulties in maintaining the effectiveness of a knowledge visualization when contextual changes occur. To address the contextual complexities, visualization systems that support knowledge management need to provide flexible support for the creation, manipulation, transformation and improvement of visualization solutions (Bai, White, Sundaram, 2012).

Janicke e Chen (2010) states a good InfoVis guides the observer's attention to the relevant aspects of the representation. Hence, the distribution of salience over a visualization image, for example, is an essential measure of the visualization's quality. Visual salience measures how much an item is distinct from neighboring items. The higher this value, the more visual attention the item attracts. This suggests that visualization's effectiveness can be improved by having a desired level and salience spatial location in the visualization. This also suggests that a measure of the salience's "appropriateness" should be a quality metric for visualization. Visual salience provides the human vision system with stimuli that attract our attention, facilitating selective analysis. Neural mechanisms and computational models of visual salience have been extensively studied in several disciplines, including neuroscience, physiology, psychology, and computer vision (Janicke, Chen; 2010).

Lurie and Mason (2007) argue that managers using interactive visualization tools rather than static representations, for example, are more likely to consider multiple factors, and thus use more compensatory processing strategies to make more accurate decisions. At the same time, the researchers warn that these tools also have the potential to bias decisions by focusing attention on a limited set of alternatives, increasing the salience of less diagnostic information, and encouraging inappropriate comparisons. Thus, the effectiveness of interactive visualization tools is limited to the extent to which they can facilitate decision processes that are both efficient and effective.

Judgment, decision-making and marketing research not only suggests a fit between representation type and task but also indicates that the optimal characteristics of a given representation may vary across tasks. These optimal characteristics include the number of alternatives presented, their organization e.g., by outcome or alternative, and the manner in which they are framed (Dilla, Janvrin, Raschke; 2010).

Consequently, well-designed visual representations can replace cognitive calculations with simple perceptual inferences and improve comprehension, memory, and decision-making. Creating visualization requires a number of nuanced judgments. One must determine which questions to ask, identify the appropriate data, and select effective visual encodings to map data values to graphical features such as position, size, shape, and color. The challenge is that, for any given data set, the number of visual encodings and thus, the space of possible visualization designs, is extremely large (Heer, Bostock, Ogievetsky; 2010).

InfoVis plays a crucial role in people's interaction with computers. Specifically, information visualization represents data or concepts graphically and helps people construct cognitive maps i.e., mental representations of the information space. Well-designed information visualization methods enable users to employ their mental capabilities to manipulate an information space and perceive it based on good mental health. Because information visualization is mediated through a person's mental capability, the space manipulation capability should be positioned to play a richer role in such interactions than it currently does (Wu, Hsu; 2011).

However, guidelines for space design manipulation remain significantly less developed than in information visualization systems. A well-designed interface for information visualization can transform the generated results, in which valuable patterns are hidden, into a format that analysts can use to explore. Analysts can also use this format to understand the knowledge in both aesthetic and cognitively ergonomic means (Card, Mackinlay, Shneiderman, 1999; Foley, 2000; Gershon, Eick, Card, 1998).

4.3.2 Pre-Purchase Online Information Seeking

Consumer information seeking is a crucial component of the purchase decision process. This process is typically comprised of steps evolving from problem recognition, onto information search, before evaluating alternatives, in order to formulate a purchase decision (Bettman et al., 1991; Olshavsky, 1985; Schmidt & Spreng, 1996). This information search is one of the most persistent topics in consumer research (Beatty & Smith, 1987) and the literature is divided into three major streams regarding consumer information search models (Srinivasan, 1990):

motivational/psychological approach, the economic approach (using a cost-benefit framework for information search) and the information processing approach. Schmidt & Spreng (1996) suggest that this third category, information processing, is encompassed in the motivational/ psychological approach, which includes both motivation and ability to search. They further include the economic approach in their model by considering costs and benefits of search to be antecedents of the motivation to search.

The amount and cost of information search may differ depending on the type of good a consumer is seeking. Here it is useful to elucidate the difference between a search and experience goods to illustrate this discrepancy. According to Nelson (1970)'s classification, a search good has a majority of attributes for which information can be acquired prior to purchase, such as price or model. In contrast, an experience good is dominated by attributes for which the value cannot be ascertained before purchase and use of the product, such as quality. From the economic approach of a cost/benefit framework to information search, Nelson (1970) states that, in an offline setting, information about quality differs from information about price because the former is usually more expensive to buy than the latter. In this sense, a product is also considered an experience good when the cost of information search is greater than experiencing the product directly.

Consumer information seeking has been the focus of numerous articles in the consumer behavior, economics, and marketing literature over the past three decades (Beatty and Smith 1987, Moorthy et al. 1997,Punj and Staelin 1983, Klein and Ford 2003). In recent decades, there have been many investigations into consumer search behavior in a digital environment (Chatterjee and Yawei 2010, Samuel 2009, Chatterjee 2010, Jepsen and Lund 2007, Wu and Rangaswamy 2003, Cambell et al. 2005, Wu et al. 2004, Rose, Grant et al. 2007, Spink et al. 2002,) and in the context of search attributes (Lynch and Ariely 2000, Klein 1998, Degartu et al. 2000).

Recently, there has been research into internet-based market efficiency (Brynjolfsson and Smith 2000), price sensitivity (Lynch and Ariely 2000, Degartu et al. 2000) and search costs (Alba and Hutchinson 1997, Lynch and Ariely 2000, Wu et al.2004). There is also much research studying the use of web search engines (Jansen and Pooch 2001, Montgomery and Daulotsis 2001, Spink et al. 2002).

It is clear information sources used by the consumers pre-purchase information search is an interesting topic from both the academic and practical point of view. At present, consumers have a number of different sources at their disposal. Conventional sources, such as advertising, newspaper and magazine advertisements, radio and television commercials, and brochures have been complemented during the last decade by information sources implemented using Internet technology. For many people, searching and comparison-shopping on the Internet is increasingly a daily behavior. The Internet has made enormous amounts of information available to consumers. While the total amount of information available to consumers increases the ability to absorb, it remains limited, leaving many consumers at a loss with regard to purchase decisions (Ariely, 2000).

The importance of studying the search for information is due because it is frequently executed in relation to purchases (Urbany, Dickson and Wilkie 1989), yet, consumers tend to limit the search to a handful of products and vendors (Öörni 2003), because search takes time and effort, and thus is costly.

The study of consumer choice and decision processes has been an active topic in consumer behavior research for over 50 years (Katona and Mueller 1955, Howard and Sheth 1969, Bettman 1979). While pre-purchase search has received considerable academic attention during the decades it is still a high priority topic and recently even gaining in importance as increasing internet penetration dramatically expands many markets and allows consumers to change their information search behavior.

Moorthy et al. (1997) suggest that the benefit of search to a consumer comes from what the authors refer to as “problem framing” as well as “involvement” and the consumer’s level of risk aversion. Problem framing represents the consumer’s uncertainty amongst the different considered options (choice environment) while involvement pertains to the importance a consumer gives to a product category. Ultimately, the pre-purchase information search should serve to reduce uncertainty amongst options so as to quell a consumer’s aversion to risk. Uncertainty can be further classified as either choice or knowledge uncertainty, each having a different effect on search activities (Urbany, Dickson, & Wilkie, 1989). Uncertainty in choice intentions (choice uncertainty) relates to the ambiguity in selection of a particular product or brand, whereas knowledge uncertainty refers to ambiguity about the products or brands themselves and even the criteria on which to evaluate each option. Urbany, Dickson, & Wilkie (1989) found that choice uncertainty increased search activities while knowledge uncertainty was potentially associated with higher search costs which, in turn, are suggested to have a negative relationship with search activities.

4.3.3 Prior Research on Type of Search and Depth of Field

4.3.3.1 Type of Search

As mentioned earlier, two main types of online seeking activities can be identified: browsing and directed search. Browsing is a seeking activity that is associated with situations in which the consumer is uncertain about the information available and is unsure whether his shopping requirements can be met, hence seeking out information in an exploratory fashion (Detlor et al., 2003; Rowley, 2000). In the case of directed search, the consumer has fairly specific requirements (Rowley, 2000) and is actively seeking out information with the intent of making a decision (Detlor et al., 2003). In this sense, directed search is more goal-oriented than browsing activities.

The goal-orientation of a consumer performing an online seeking activity is important as it can point to the type of information processing employed. Chernev (2003a) postulated that consumers with clearer preferences are more probable to use an ideal attribute combination when evaluating alternatives. Here, the ideal attribute combination represents a combination of product characteristics that best represent the preferences of the consumer and hence indicative of information processing by alternative. In contrast, those without these clear preferences or ideal attribute combination to compare alternatives, are more probable to use attributes of various alternatives for comparison (Simonson & Tversky, 1992) indicating information processing by attribute. Essentially, it would seem that those with a clear goal in mind when searching are more likely to use alternative- based processing whereas those that do not seem to favor attribute-based processing. In addition, Detlor et al. (2003) remarked that consumers who were in a directed-search mode preferred detailed product information in terms of product specifications, although it is unclear if this indicates a preference for alternative-based processing.

Rowley (2000) suggested that consumers refine their strategies and information requirements as they consider information gathered throughout the search process. This refinement may cause a gradual shift from an exploratory browsing mode to a more focused directed search (Shim, Eastlick, Lotz, & Warrington, 2001). The viewpoint of phased information seeking activities seems analogous to previously described phased strategies or combined heuristics (Bettman, 1979; Bettman et al., 1991) whereby one decision strategy is first used to eliminate alternatives and then another strategy adopted to compare the remaining options in the choice set. In a more recent study, Montgomery, Li, Srinivasan, and Liechty (2004) propose a model of web browsing that accounts for the two states of navigation, browsing and directed search. Their model acknowledges that a user may switch between these two information seeking activities many times during a visit to a website "depending on the user's current goals or state of mind" (p. 584). The proposed dynamic change between browsing and directed search departs from the notion of sequential shifts from one mode to the next and seems tantamount to the observed switching between information processing types (Shi et al., 2013) previously described.

4.3.3.2 Depth of Field

Lurie and Mason (2007) use the term "visual perspective" to refer to how a given visual representation changes the relation between visual information and the decision maker. The authors state that the first aspect of visual perspective is "interactivity," or the user's ability to change perspective, for example, by rotating or simulating movement around an image. The second aspect of visual perspective is "depth of field," which refers to whether a tool provides context by displaying an overview of large numbers of data points and/or more focused detail information on particular data points of interest.

Visual representations vary in depth of field, which is the extent to which visual representations provide contextual overview versus detail information or enable decision makers to maintain both levels in focus simultaneously (Lurie and Mason, 2007). Depth is likely to affect how information is accessed and evaluated (Ganapathy, Ranganathan, and Sankaranarayanan, 2004).

However, visualization tools that deliver more context rather than more detail, and tools that enable more alternatives to be displayed in a given visual field, may lead to relatively less compensatory (more selective) decision processes as decision makers eliminate alternatives from consideration (Payne 1976).

Lurie and Mason (2007) discuss other approaches to combining context and detail such as using: different windows to provide both overview and detailed views (Beard and Walker 1990); bifocal views, in which centrally located information is magnified and peripheral information is presented in a demagnified or bill-board format (Robertson and Mackinlay 1993; Spence and Apperley 1982); and fish-eye views, which distort information such that focal information is larger and nonfocal information is smaller (Sarkar and Brown 1994). Some results show faster navigation and data identification when an overview is provided. However, others have found that, although user satisfaction is higher, navigation may be slower because of the additional cognitive load of addressing simultaneous views (Hornbæk, Bederson, and Plaisant 2002).

Hornbæk and Frøkjær (2001) find that offering both overview and detailed views increases the general understanding of content, that detailed views only lead to superior speed in answering explicit requests and that fish-eye views increase reading speed. This suggests that whether combining context and detail is superior to either one alone depends on whether the goal is to maximize accuracy or minimize effort. In particular, visual representations that provide contextual information should lead to more consistent preferences than those that do not. However, such representations are likely to involve greater decision-making effort and time.

Examination of sequences of information acquisition from an information display during external information search have revealed two type of information acquisition, either by alternative or by attribute. In alternative-based processing, the information on multiple attributes of an alternative is obtained and considered before moving to the next alternative. Conversely, in attribute-based processing, information is obtained on a single attribute for multiple alternatives. To demonstrate the difference, consider a consumer who is shopping for a new computer tower on the Dell website. If the consumer is acquiring information via alternative-based processing, when viewing the list of tower models available and all of their specifications, he would then be obtaining information regarding the processor speed, memory capacity, hard drive space, etc. for a single tower model before moving to the next model for comparison. In contrast, if the consumer is acquiring information through attribute-based processing, he would investigate a single attribute of a first tower model, for example processor speed, before moving to the next model to examine the same attribute for comparison.

Interestingly, it has been asserted that the format of the information display strongly affects the type of information processing employed (Bettman, 1979). Furthermore, many foundational decision-making theories postulate a sequential shift in the type information-processing by a consumer when making a choice (Howard & Sheth, 1969; Newell & Simon, 1972; Payne, 1976). In this case, the consumer first assumes attribute-based processing to screen out certain options and then switch into alternative-based processing to evaluate the remaining alternatives in the choice set for a final selection. In contrast to this notion of sequential shift between these two information-processing types, a more recent online study by Shi et al. (2013) demonstrated a high incidence of switching between acquisition states. It was noticed, in the study, that participants limited attention to roughly three attributes for an alternative and about two alternatives for a single attribute. Furthermore, the experiment revealed that the information collected on attributes induced switching away from alternative-based processing while information collected on alternatives induced switching away from attribute-based processing. This suggests that instead of the sequential shift in information processing from attribute to alternative-based as previously stated, consumers may sample parcels of adjacent product and attribute information (Shi et al., 2013).

Product comparisons at the heart of decision strategies are preceded by information seeking activities, whereby a consumer forms a choice set. It has been suggested that, like information processing, these information seeking activities also change as consumers refine their information requirements (Rowley, 2000).

Interestingly, much of the literature on decision-making theories suggest that decision strategies employed in making a choice are not mutually exclusive but rather used together sequentially (Howard & Sheth, 1969; Newell & Simon, 1972; Payne, 1976). In other words, a consumer is postulated to first adopt an attribute- based decision strategy to eliminate certain options followed by the adoption of an alternative-based decision strategy to evaluate the each of the remaining options to arrive at a final choice. In contrast to this notion of the sequential use of these two information processing types for decision-making, an experiment using eye- tracking technology by Shi, Wedel, and Pieters (2013), demonstrated a high incidence of switching between attribute and alternative-based modes of information processing, when navigating an e-commerce site with the intent to make a purchase. Here, participants seemed to consider clusters of attribute and product information with the amount of information gathered on attributes inducing a switch away from alternative-based information processing. Conversely, information gathered on products induced a switch away from an attribute-based mode of information processing (Shi et al., 2013).

When faced with a choice task, decision makers select an alternative from a set of alternatives presented to them. An example of a choice task would be the selection of a product in an online shop or the selection of a specific applicant among a variety of applicants. When choosing among alternatives, decision makers follow a decision strategy, which is defined as a “set of operations used to transform an initial stage of knowledge into a final goal state of knowledge where the decision maker feels the decision problem is solved” (Payne, Bettman, Coupey, & Johnson, 1992, p. 108). Decision makers do not always follow the same decision strategy but rather adaptively select from a repertoire of different decision strategies (Payne, Bettman, & Johnson, 1993; Riedl, Brandstätter, & Roithmayr, 2008, Pfeiffer, 2014).

The choice of the decision strategy used is determined by (a) the decision makers' personal characteristics (e.g., cognitive ability, the decision makers' prior knowledge), (b) the social context (e.g., accountability, group membership), and (c) the characteristics of the problem such as task-based complexity and context-based complexity (Payne et al., 1993). Task-based complexity captures the general aspects of a choice task, such as the amount of information (e.g., number of alternatives or attributes) and the way it is presented. Context-based complexity is user-specific and assesses whether particular attribute levels and their relationship to one another make a choice task difficult for a particular decision maker (Payne et al., 1993; Swait & Adamowicz, 2001; Pfeiffer, 2014).

Prominent examples of variables that are used to measure context-based complexity are the similarity of alternatives and the conflict of alternatives. A conflict occurs when trade-offs force the decision maker to balance one attribute level against another. While there is a huge body of literature concerning the influence of task-based complexity on decision-making behavior (Bettman, Johnson, & Payne, 1991; Payne et al., 1992), mostly stemming from psychological research, there is only limited research about the influence of context-based complexity on the decision process (Fasolo, Hertwig, Huber, & Ludwig, 2009; Bettman, Luce & Payne, 1997). In contrast to the finding that each decision maker may value the same attribute levels differently (Böckenholt et al., 1991; Keller & Staelin, 1987; Russo & Dosher, 1983; Swait & Adamowicz, 2001), most studies on the influence of context-based complexity on decision processes neglect the existence of individual preference structures and assume that attribute level utilities are equal for different decision makers (notable exceptions are Russo and Dosher (1983); Böckenholt et al., (1991), and Bettman, Luce & Payne (1997)). The resulting inaccurate measurement of context-based complexity might also be a reason why most studies did not find an influence of context-based complexity on information search patterns.

Relevant measures for context-based complexity of choice tasks are *similarity* and *conflict* among attributes (Bettman, Luce & Payne 1997; Payne et al., 1993; Swait & Adamowicz, 2001). Similarity captures the degree to which alternatives differ from each other and is typically either operationalized by the variety of attribute level utilities per attribute (attribute range) (Bettman, et al., 1993; Biggs, Bedard, Gaber, & Linsmeier, 1985; Fasolo, Hertwig, et al., 2009; Payne et al., 1993), or the difference of the alternatives' total utility values (attractiveness difference) (Swait & Adamowicz, 2001).

Previous studies that focused on the influence of context-based complexity on decision-making behavior (except Russo and Dosher (1983) and Luce et al., (1997)) did not measure individual attribute level utilities (Bettman et al., 1993; Biggs et al., 1985; Iglesias-Parro, la Fuente, & Ortega, 2002; Payne, Bettman, & Johnson, 1988; Pfeiffer, 2014).

Consumers increasingly acquire information and make decisions about products online. The way in which they gather information affects their decisions. Web retailers and manufacturers recognize this and try to optimize online information displays to facilitate and direct choices. These online information displays often take the form of attribute-by-product matrices, which have become popular, especially on comparison sites (for instance, Bizrate.com, Dell.com, and Nextag.com all have more than 10 million monthly visitors). These websites mainly use vertical and horizontal formats for presenting information: for example, as a default, Bizrate.com uses a horizontal format with products presented in the rows, and Dell.com uses a vertical format with products presented in the columns. (Shi, 2013)

Studies with process tracing methods (Payne et al. 1993) have revealed two key processes that consumers use to acquire information on such displays: attribute based and product based (Ball 1997, Bettman et al. 1998, Payne et al. 1993). During attribute-based acquisition, information is obtained on a single attribute across multiple products before proceeding to the next attribute. During product-based acquisition, information is acquired on a single product across multiple attributes before proceeding to the next product. In theories of decision making, consumers are postulated to first adopt attribute-based acquisition to screen out certain products and then switch to product-based acquisition to evaluate the remaining products and make their final choice (Howard and Sheth 1969, Newell and Simon 1972).

Thus, the idea is that the use of the two information acquisition processes over time is linked to different decision-making stages, and people switch once or twice between these processes. The presentation format has been shown to affect information acquisition: a horizontal format induces more product-based processing and a vertical format more attribute-based processing (Bettman and Kakkar 1977). The managerial implications of this foundational research (Bettman et al. 1998, Payne and Venkatraman 2011, Weber and Johnson 2009) are becoming more significant because of the increased use of product-comparison matrices online (Shi, 2013).

4.3.4 Eye movements and Decision Making

A consumer's eye movements can be measured by employing an eye tracking technique to monitor both where a person is looking at any given time (fixation) and the sequence in which their eyes shift from one location to another (saccade). Eye fixations are regarded as information acquisition responses and tracking eye fixations is the most efficient way to obtain information on humans from the environment. Cognitive processing can be categorized into two types of activity: the acquisition of information and the operations that are performed on this information. For example, consumers' decision making, or strategy for performing a cognitive task, will exhibit a characteristic pattern of information acquisition and internal computation. Fixations, however, can be interpreted differently depending on the context. For instance, a longer fixation duration could indicate difficulty in extracting information or it could mean that the object is more engaging in a certain situation (Just and Carpenter, 1976).

In addition, higher fixation frequency can be indicative of greater interest in the target (e.g. a photograph in a magazine) in an encoding task or can be explained as an index of greater uncertainty in recognizing a target item in a search task (Jacob and Karn, 2003). The relationship between eye movements and cognitive processes has been studied extensively (Henderson, 2003; Kowler, 1990), and the most novel finding of task-oriented studies is that the eyes are positioned at a point that is not the most visually salient but is the best for the spatio-temporal demands of the job at hand. Ripoll et al. (1995) analyzed the information processing and decision making of boxers with various levels of expertise by employing an eye movement recorder (Ripoll et al., 1995).

By analyzing the spatial-temporal characteristics of the visual search activity, they showed a significant correlation between the level of expertise and participants' visual strategy. Russo and Leclerc (1994) examined the nature of the choice process for commonly purchased non-durables by tracking eye fixations and suggested that the process contains three stages: orientation, evaluation, and verification (Russo and Leclerc, 1994). The duration of a fixation is linked to the processing time applied to the object being fixated upon (Just and Carpenter, 1976). Although not observable, specialized computations occur during fixations. Highly task-specific information is extracted in different fixations, and these task-specific computations are indicated by the duration of the fixations, which vary widely (Pelz and Canosa, 2001). A large part of this variation relies on the particular information required for that point in the task, with fixation terminated when the particular information is acquired (Hayhoe et al., 1998; Henderson, 2003; Chae & Lee, 2013).

Prior process tracing studies of consumer decision making have used methods such as information display boards, Mouselab and Flashlight (see, for example, Costa-Gomes and Crawford 2006, Willemsen et al. 2011), in which information becomes available sequentially through manual inspection, such as mouse clicking or card turning. This renders the choice process in those studies more controlled and deliberate. However, comparison websites provide all attribute information of all choice options simultaneously.

Information acquisition is then fast and governed by automatic processes. The simultaneous availability of information may also allow more flexible switching between information strategies than can be detected with more traditional process tracing methods. Eye-tracking methodology is particularly suited to provide insights under these conditions (Lohse and Johnson 1996, Russo 1978, Schulte-Mecklenbeck et al. 2011). Because of technological advances, eye tracking is now widely used in academia and practice (Wedel and Pieters 2008). Eye-movement data consist of eye fixations, which are brief moments that the eye is still and information is extracted from the stimulus (about two to four times per second); saccades are rapid jumps of the eye between fixations to redirect the line of sight to a new location (Shi, 2013).

Although introspection may suggest that information acquisition on comparison websites is a fairly well structured and orderly process, as will become clear below, the data collected in our experiment indicate a different conclusion. That is, whether information acquisition is attribute based or product based is often not immediately discernible from the large volumes of dense eye fixation data, and it is difficult to assess precisely how these two strategies are used over time and what information is acquired. The main aim of our research is therefore to develop a model-based approach that facilitates inferences about these rapid attribute and product-based information acquisition processes during decision making as well as the switching between these processes, recognizing that they are fundamentally unobservable. Information acquisition processes are latent cognitive states that direct the eyes in a search for information on the display. Eye movements reflect these states probabilistically rather than deterministically (Lohse and Johnson 1996, Wedel and Pieters 2000; Shi, 2013)

In spite of the growth of interest in using eye movements to better understand and predict choice behavior (see, for example, Pieters and Warlop 1999, Reutskaja et al. 2011, Russo and Leclerc 1994, Stüttgen et al. 2012), research on information acquisition on attribute-by-product displays such as used in comparison sites is as yet limited. Whereas research using traditional process tracing methods has shown that consumers sequentially use two stages (screening and evaluation) in decision making, in an analysis of eye and head movements of packages on a simulated shelf, Russo and Leclerc (1994) characterized the decision process as comprising three stages: screening, evaluation, and verification. Screening consisted of a serial inspection of mostly adjacent products, evaluation involved the comparison of a limited set of remaining products, and during verification the chosen product was compared with others.

Research suggests that people switch between attribute and product-based information acquisition processes when the demands of the task change (Ball 1997, Payne 1976, Pieters and Warlop 1999, Swait and Adamowicz 2001), for example, because of experienced accuracy and effort (Bettman et al. 1998) as a function of the information already acquired up to that point (Bettman and Park 1980, Russo and Rosen 1975). However, the extent of switching in natural tasks such as online choice has not yet been quantified. (Shi, 2013).

4.3.4.1 Eye-Tracking

Process-tracing approaches have been used in studies on decision-making (e.g. Jacoby, Chestnut, Weigl, & Fisher, 1976; Payne, 1976; Payne, Bettman, & Johnson, 1988), where the study authors try to measure the decision process directly without interfering it. A variety of process-tracing techniques exist such as verbal protocols, information display boards and tracking eye movements. In the past, eye-tracking technologies have been criticized for their obtrusive and expensive apparatuses, which restricted a subject's head movements and difficulty in localizing eye movements (Bettman, 1979).

Today, advances in eye-tracking have rendered the apparatuses unobtrusive and virtually unnoticeable to a user whose eye movements are being captured. As well, the data yielded from these types of experiments is vastly more accurate than previously and allow detailed analysis of captured eye movements. Eye movements are relatively effortless and so encourage information acquisition from the stimuli.

In contrast, other process tracing techniques (such as verbal protocols) require relatively more mental effort and may encourage use of information already stored in memory hence becoming unobservable in an experimental setting (Russo, 1978). In view of these improvements in eye-tracking and the ability to observe information acquisition without disturbing the information search process, this is the method elected for this study. Below is a description of the properties and use of this technology.

4.3.4.2 Eye Movements and Eye-tracking

In order to further elucidate the utility of eye-tracking tools and measures, it is important to briefly describe eye movement types and the technology used to record them. Rayner (1998) makes summary of eye movements and their cognitive implications. Eye movements generally consist of two types: saccades and fixations. Saccades are rapid eye movements during which sensitivity to visual input is reduced. Fixations occur between saccades, when the eyes remain still for 200-300 ms. The visual field consists the fovea, parafovea and peripheral regions. The fovea consists of the central 2° of the field of vision, where visual acuity is the highest. The parafovea extends 5° outward from either side of the fixation and visual acuity drops significantly from the fovea. The peripheral region lies beyond the parafovea to complete the visual field and acuity is lowest in this region.

The limitations of our visual field dictates eye movements as we look to derive more information from a particular stimulus. By placing the foveal region of vision on a stimulus we can see it clearly and get the most visual information available. Saccades are made to stimuli in the parafoveal or peripheral region of the visual field to determine if these should become the new focus of the foveal region for greater information (Rayner, 1998). Research has shown that two separate neural pathways are involved in object localization and identification (Ungerleider, 1982) and produce different eye-movement patterns. Seeing as humans have limited information processing capabilities, attentional mechanisms are needed to select relevant information from the field of vision. This “where” (localization) and “what” (identification) in a visual stimulus requires us to focus attention on one or the other (Van Der Lans, Pieters, & Wedel, 2008). This can be useful when trying to derive the cognitive state via eye movements with more dense fixations during localization (Van Der Lans et al., 2008).

Information acquisition processes, such as the information processing types seen earlier, are “latent cognitive states that direct the eyes in a search for information on the display” (Shi et al., 2013, p. 2). Wedel and Pieters (2000) caution that eye movements are indicative of these states in a way that is probabilistic more than deterministic. In so far as the mechanism involved in switching between the two modes of information processing (alternative or attribute based), it seems to be the result of sampling of bits of information by the decision maker. It is interesting to note that Shi et al.(2013) underline the fact that information sampled is contiguous on the display. In this sense the eyes do not need to travel very far to fixate on the next meaningful piece of information to aid decision-making.

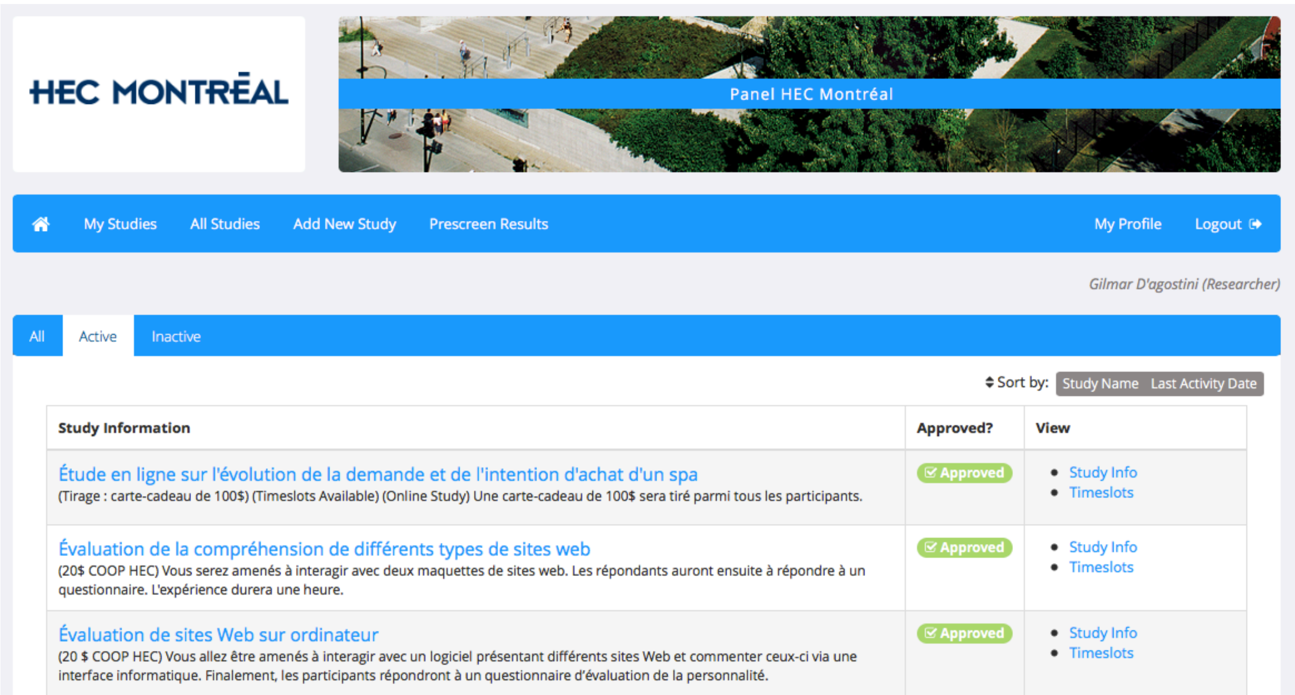
4.4 Experiment 1

4.4.1 Method

4.4.1.1 Participants

Thirty-four (34) individuals recruited largely via HEC Student Panel participated in this study, and each participant was paid 20 Canadian Dollars as compensation. We also had some participants through direct solicitation by the research directors, lab technicians and the researcher. Participants registering through the HEC Student Panel (Fig. 10) were able to select timeslots according to their availabilities and those of the lab. To minimize no-show occurrence, participants were given reminders via a call 48 hours before their scheduled timeslot and an email to the same effect, sent 24 hours beforehand.

Figure 10 - Example of how participants registered to participate in this study.



After eliminating four participants due to incomplete measures, the analyses were conducted with the remaining participants (N = 30). The average age was 20.4, and 60% were females. We received written informed consent from all participants, in accordance with HEC Montréal Ethics Board approval for this project (Appendix 4).

4.4.1.2 Design and Stimuli

A within-subjects design 2 (Depth-of-Field: Products presented by Attribute, *AT;* Products presented by Alternative, *AL*) X 2 (Type of Search: Goal Oriented, *GO;* Browsing, *BR)* was performed to analyze how different ways of product's information presentation can influence individual online information seeking behavior. This resulted in four different experimental conditions, e.g.: GO_AT, indicating that this condition was a Goal Oriented and Attribute situation, and so on.

The study was operationalized and collected using Tobii Pro Studio, and Qualtrics softwares from participants in an experimental laboratory in a Canadian university. The first screen of the experiment provided clarification and the generic objective of the study.

To make the participants experience in an online retail environment appear real, scenarios were presented using a webpage from a leading computer/notebook store in the e-commerce segment in Canada in partnership with the laboratory where research was conducted. The first variable (Depth-of-Field) was manipulated by changing how the information of a product was presented, if showing information by attributes (Figure 11) or by alternatives (Figure 12). The second independent variable was manipulated in the text presented to participant before he/she accessed each of the four webpages. The instruction varied accordingly to manipulations, to reflect a browsing situation ("Imagine you are navigating on the web and accessing the following webpage…") and a purchase task ("Imagine you have to buy a personal computer for yourself, …").

Figure 11 - Example of Products by Attributes

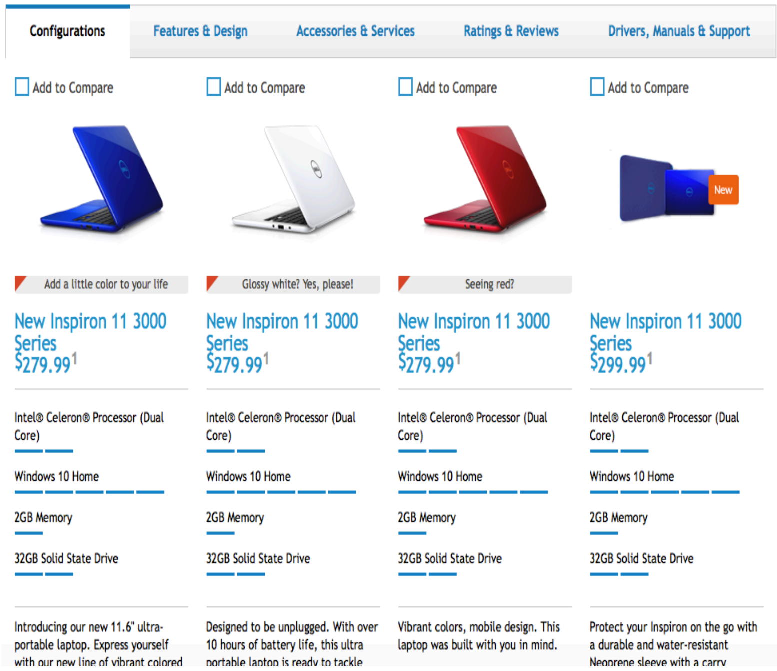
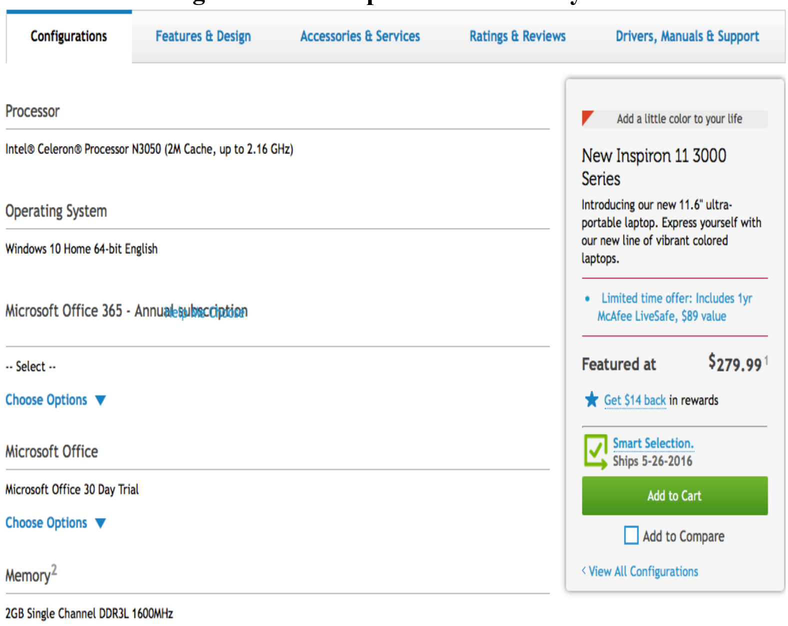


Figure 12 - Examples of Products by Alternative



4.4.1.3 Procedure

Participants were welcomed individually, by appointment, at the laboratory. After all initial procedures (presentation, acceptance term, calibration of equipment…), participants were asked to participate in an academic research and to follow the instructions on the screen. They were exposed to four different conditions assigned randomly within subjects. After each of the four webpages, participants answered a questionnaire containing some behavioral measures (see below). After each of the four stimuli, participants responded to measures of the dependent variables. Thereafter, demographic, realism of the scenario and manipulation check questions were collected. Finally, the debriefing was held and participants received the monetary compensation along with a final consent informing the end of the study and that monetary compensation was properly delivered.

4.4.1.4 Measures

This study used two different types of measurements: a manipulation check measure, used to verify the effectiveness of the manipulation of the independent variables; and the dependent variables measures, i.e., information acquisition and visual appeal measures.

4.4.1.4.1 Manipulation Check

For the manipulation check, it was questioned to the participant, at the end of the experiment, if information was presented to them in different ways of visualization. According to the data, everyone confirmed data were presented differently, and, when asked the aim of this research none of them got the right answer.

4.4.1.4.2 Dependent Variables

Many variables were considered in this study. It was expected direct effects of the treatments on (1) Information Quality, (2) Information Acquisition, (3) Visual Appeal, and (4) Intention to Revisit. All variables were measured by scales used in other studies and established in the literature as follows.

Information Quality scale used in this article is part of WebQual 4.0 Scale, from Barnes and Vidgen (2002). Participants rated on a eight-point scale (disagree – agree) the following statements: The webpage I've seen… a) "has sufficient contents where I expect to find information"; b) "provides complete information"; c) "provides site-specific information"; d) "provides accurate information"; e) "provides timely information"; f) "provides reliable information"; and, g) "communicates information in an appropriate format".

The Information Acquisition was measured by a modified scale from Murray (1991) study. Participants rated on a seven-point scale (totally disagree – totally agree) the following statements: a)

"I paid attention to what previous costumers said about the product in this page"; b) "I am ready to make a purchase selection and not worried about acquiring more information prior to buying"; c) "I have much more information about the product after visiting this page"; d) "I was able to see different kinds of information provided by the seller"; e) " I tried to recall relevant events which I can associate with this product or service".

Additionally, the Visual Appeal was measured using a scale from the Lindgaard et al. (2006) study. In this scale, the following items generate the most reliable and valid measure of "visual appeal." Participants rated these on a nine-point scale: a) interesting – boring; b) good use of color – bad use of color; c) well designed – poorly designed; d) good layout – bad layout; and, e) imaginative – unimaginative. A combination of these five items predicted, according to Lindgaard et al. (2006), 94% of visual appeal ratings for website homepages.

According to Netemeyer et al. (2004), it was also asked participants intention to revisit (for all conditions) using a five-points scale (very unlikely – very likely).

4.4.2 Results

In order to examine if Depth-of-Field and Type of Search would be responsible for creating a difference in means on a) intention to revisit; b) information quality; c) visual appeal; and, d) information acquisition, we performed a series of repeated-measures ANOVA using IBM SPSS package.

Table 2 shows the descriptive statistics for every dependent measures considered in this study:

Table 2 – Descriptive Statistics (for all dependent variables)

Factors		Intention to Revisit	Information Quality	Visual Appeal	Information Acquisition
B_ALT (N=30)	**Mean**	**4.0714**	**6.8112**	**3.6**	**5.7232**
	SD	0.53945	0.81097	1.37706	1.09151
B_ATT (N=30)	**Mean**	**3.4688**	**6.5982**	**4.4**	**5.375**
	SD	0.80259	1.16535	0.91722	1.22967
GO_ALT (N=30)	**Mean**	**2.9375**	**5.7321**	**4.2187**	**4.1172**
	SD	1.04534	1.39724	1.56276	1.20145
GO_ATT (N=30)	**Mean**	**3.3214**	**6.1276**	**5.1571**	**4.6786**
	SD	1.0203	1.23341	1.11602	1.26903

Source: Research Data

All measures were composed of the mean absolute difference between the ratings each subject gave to each scale after being exposed to one of the four conditions. Because one of the main objectives of the experiment was to examine changes in these DVs level for the same participant, the rating-error measure was based on the mean absolute differences for each individual trial.

The following table shows the one-way repeated-measures ANOVA data statistics (Table 3):

Table 3 - Repeated Measures ANOVA (for all dependent variables)

	Dependent Variables	Type III Sum	df	Mean Square	F	Sig.
Factors	Intention to Revisit	2.663	2.444	1.089	1.374	0.003
	Information Quality	4.61	2.217	2.079	1.784	0.027
	Visual Appeal	3.23	2.645	1.221	1.148	0
	Information Acquisition	4.067	2.189	1.858	1.564	0.008
Error (Factors)	Intention to Revisit	56.196	70.884	0.793		
	Information Quality	74.931	64.298	1.165		
	Visual Appeal	81.58	76.7	1.064		
	Information Acquisition	75.402	63.477	1.188		

Source: Research Data

Intention to Revisit. A repeated measures ANOVA with a Greenhouse-Geisser correction determined that means for this variable differed statistically significantly between conditions (F(2.444, 70.884) = 1.374, *P* = 0.003). Post hoc tests using the Bonferroni test (Table 4) revealed that for participants the intention to revisit the webpage which was presented the products by alternative, and after a browsing task, B_ALT (M = 4.0714, SD = 0.53945), differed statistically significantly from all other conditions like B_ATT (M = 3.4688, SD = 0.80259, p = 0.045), GO_ALT (M = 2.9375, SD = 1.04534, p < 0.001), and GO_ATT (M = 3.3214, SD = 1.0203, p = 0.01). Figure 13 represents the effects of the factor on the intention to revisit that webpage.

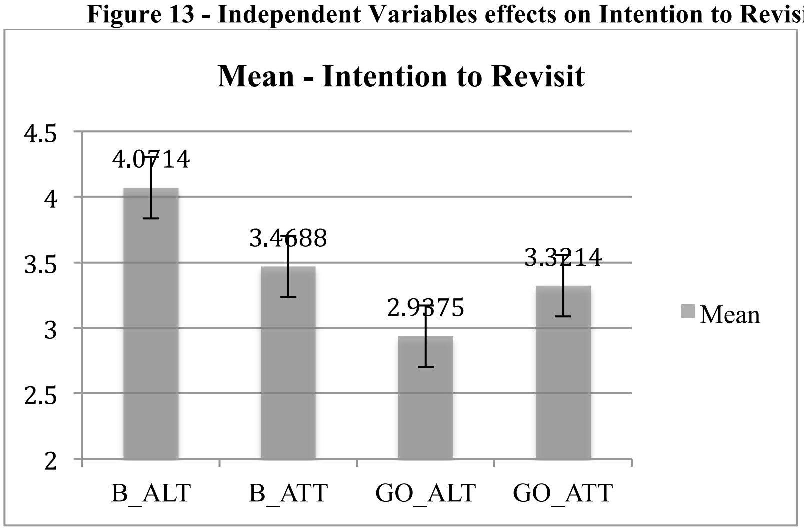
Table 4 - Pairwise Comparisons: Intention to Revisit

(I) Factor	(J) Factor	Mean Difference (I-J)	Std. Error	Sig.a	95% Confidence Interval LB	95% Confidence Interval UB
B_ALT	B_ATT	.60268*	0.22769	0.045	0.0092	1.1962
	GO_ALT	1.13393*	0.22769	0	0.5404	1.7274
	GO_ATT	.75000*	0.23516	0.01	0.137	1.363
B_ATT	B_ALT	-.60268*	0.22769	0.045	-1.1962	-0.0092
	GO_ALT	0.53125	0.21997	0.08	-0.0421	1.1046
	GO_ATT	0.14732	0.22769	0.916	-0.4462	0.7408

GO_ALT	B_ALT	-1.13393*	0.22769	0	-1.7274	-0.5404
	B_ATT	-0.53125	0.21997	0.08	-1.1046	0.0421
	GO_ALT	-0.38393	0.22769	0.336	-0.9774	0.2096
GO_ATT	B_ALT	-.75000*	0.23516	0.01	-1.363	-0.137
	B_ATT	-0.14732	0.22769	0.916	-0.7408	0.4462
	GO_ALT	0.38393	0.22769	0.336	-0.2096	0.9774

Based on estimated marginal means
a Adjustment for multiple comparisons: Bonferroni.
Source: Research Data

Figure 13 - Independent Variables effects on Intention to Revisit



(Error bars indicate ±1 standard error of the mean.)

Information Quality. A repeated measures ANOVA with a Greenhouse-Geisser correction determined that means for this variable differed statistically significantly between conditions (F(2.217, 64.298) = 1.784, *P* = 0.027). Post hoc tests using the Bonferroni correction (Table 5) revealed that for participants the information quality of the webpage which was presented the products by alternative, and after a goal-oriented task, GO_ALT (M = 5.7321, SD = 1.39724) differed statistically significantly from browsing conditions, namely B_ALT (M = 6.8112, SD = 0.81097, p = 0.003) and B_ATT (M = 6.5982, SD = 1.16535, p = 0.021). Figure 14 represents the effects of the factors on the information quality perception of each webpage design.

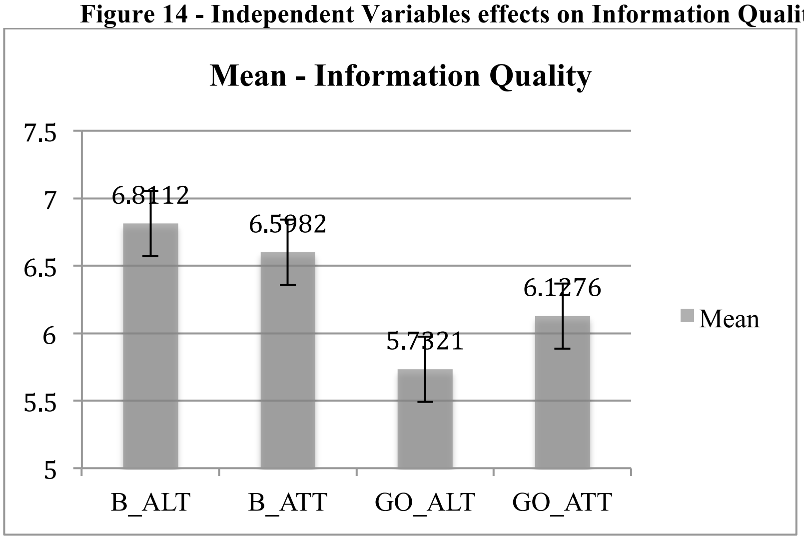
Table 5 - Pairwise Comparisons: Information Quality

(I) Factor	(J) Factor	Mean Difference (I-J)	Std. Error	Sig.a	95% Confidence Interval	
					LB	UB
B_ALT	B_ATT	0.21301	0.30529	0.898	-0.5828	1.0088
	GO_ALT	1.07908*	0.30529	0.003	0.2833	1.8749

	GO_ATT	0.68367	0.3153	0.138	-0.1382	1.5056
B_ATT	B_ALT	-0.21301	0.30529	0.898	-1.0088	0.5828
	GO_ALT	.86607*	0.29494	0.021	0.0973	1.6349
	GO_ATT	0.47066	0.30529	0.416	-0.3251	1.2665
GO_ALT	B_ALT	-1.07908*	0.30529	0.003	-1.8749	-0.2833
	B_ATT	-.86607*	0.29494	0.021	-1.6349	-0.0973
	GO_ALT	-0.39541	0.30529	0.568	-1.1912	0.4004
GO_ATT	B_ALT	-0.68367	0.3153	0.138	-1.5056	0.1382
	B_ATT	-0.47066	0.30529	0.416	-1.2665	0.3251
	GO_ALT	0.39541	0.30529	0.568	-0.4004	1.1912

Based on estimated marginal means
a Adjustment for multiple comparisons: Bonferroni.
Source: Research Data

Figure 14 - Independent Variables effects on Information Quality



(Error bars indicate ±1 standard error of the mean.)

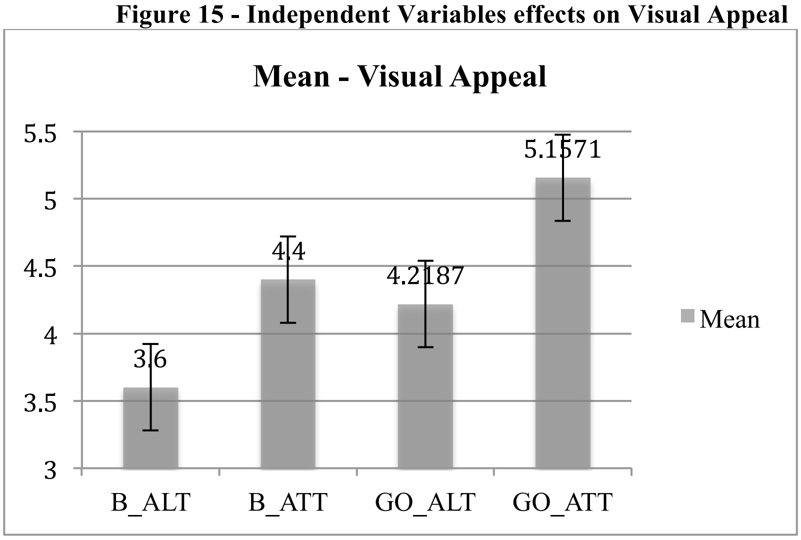
Visual Appeal. A repeated measures ANOVA with a Greenhouse-Geisser correction determined that means for this variable differed statistically significantly between conditions (F(2.645, 76.7) = 1.148, $p < 0.001$). Post hoc tests using the Bonferroni correction (Table 6) revealed that for participants the visual appeal of the webpage which products were presented by attribute, and after a goal-oriented task, GO_ATT (M = 5.15, SD = 1.11602) differed statistically significantly from conditions where products were presented by alternative, namely B_ALT (M = 3.6, SD = 1.37706, p < 0.001) and GO_ALT (M = 4.2187, SD = 1.56276, p = 0.026). Figure 15 represents the effects of the factors on the information quality perception of each webpage design.

Table 6 - Pairwise Comparisons: Visual Appeal

(I) Factor	(J) Factor	Mean Difference (I-J)	Std. Error	Sig.a	95% Confidence Interval	
					LB	UB
B_ALT	B_ATT	-0.8	0.32822	0.076	-1.6556	0.0556
	GO_ALT	-0.61875	0.32822	0.24	-1.4743	0.2368
	GO_ATT	-1.55714*	0.33899	0	-2.4408	-0.6735
B_ATT	B_ALT	0.8	0.32822	0.076	-0.0556	1.6556
	GO_ALT	0.18125	0.31709	0.94	-0.6453	1.0078
	GO_ATT	-0.75714	0.32822	0.102	-1.6127	0.0984
GO_ALT	B_ALT	0.61875	0.32822	0.24	-0.2368	1.4743
	B_ATT	-0.18125	0.31709	0.94	-1.0078	0.6453
	GO_ATT	-.93839*	0.32822	0.026	-1.794	-0.0828
GO_ATT	B_ALT	1.55714*	0.33899	0	0.6735	2.4408
	B_ATT	0.75714	0.32822	0.102	-0.0984	1.6127
	GO_ALT	.93839*	0.32822	0.026	0.0828	1.794

Based on estimated marginal means
a Adjustment for multiple comparisons: Bonferroni.
Source: Research Data

Figure 15 - Independent Variables effects on Visual Appeal



(Error bars indicate ±1 standard error of the mean.)

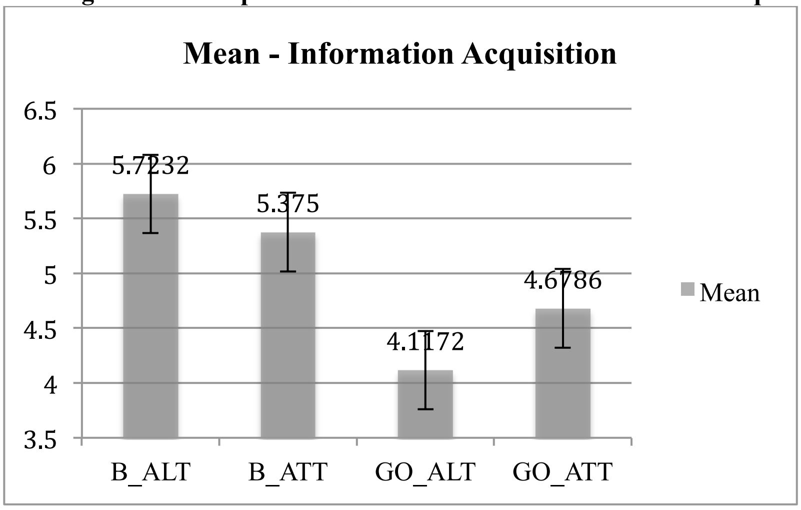
Information Acquisition. A repeated measures ANOVA with a Greenhouse-Geisser correction determined that means for this variable differed statistically significantly between conditions (F(2.189, 63.477) = 1.564, p = 0.008). Post hoc tests using the Bonferroni correction (Table 7) revealed that information acquisition after viewing each of the webpages differed statistically significantly in some conditions. When viewing products by alternative, after a browsing task, B_ALT (M = 5.7232, SD = 1.09151), participants differed in information acquisition perceptions from those situations where they were viewing products after a goal-oriented task, even by alternative, GO_ALT (M = 4.1172, SD = 1.20145, $p < 0.001$) or by attribute, GO_ATT (M = 4.6786, SD = 1.26903, $p = 0.008$). We also found difference in means between the B_ATT (M = 5.375, SD = 1.22967) and GO_ALT (M = 4.1172, SD = 1.20145) at $p < 0.001$ levels. Figure 16 represents the effects of the factors on the information quality perception of each webpage design.

Table 7 - Pairwise Comparisons: Information Acquisition

(I) Factor	(J) Factor	Mean Difference (I-J)	Std. Error	Sig.a	95% Confidence Interval	
					LB	UB
B_ALT	B_ATT	0.34821	0.31075	0.678	-0.4618	1.1582
	GO_ALT	1.60603*	0.31075	0	0.796	2.416
	GO_ATT	1.04464*	0.32094	0.008	0.2081	1.8812
B_ATT	B_ALT	-0.34821	0.31075	0.678	-1.1582	0.4618
	GO_ALT	1.25781*	0.30021	0	0.4753	2.0404
	GO_ATT	0.69643	0.31075	0.118	-0.1136	1.5064
GO_ALT	B_ALT	-1.60603*	0.31075	0	-2.416	-0.796
	B_ATT	-1.25781*	0.30021	0	-2.0404	-0.4753
	GO_ALT	-0.56138	0.31075	0.275	-1.3714	0.2486
GO_ATT	B_ALT	-1.04464*	0.32094	0.008	-1.8812	-0.2081
	B_ATT	-0.69643	0.31075	0.118	-1.5064	0.1136
	GO_ALT	0.56138	0.31075	0.275	-0.2486	1.3714

Based on estimated marginal means
a Adjustment for multiple comparisons: Bonferroni.
Source: Research Data

Figure 16 - Independent Variables effects on Information Acquisition



(Error bars indicate ±1 standard error of the mean.)

4.4.3 Discussion

This experiment examined the influence of type of search and depth-of-field in the consumer online information seeking behavior using behavioral measures. The results of the current study led to several important findings. Firstly, the intention to revisit the website is higher for those in the browser conditions when viewing products by alternative (one product at a time) than for any other condition. We explain this putting into consideration that in other conditions participants had a stipulated task, which was responsible for making them pay more attention in the website, or had more information about products (when comparing products at the "attribute" level). This, could led participants to further revisit the webpage to get more information about the product.

Also, participants visualizing the attribute conditions had a greater sensation of visual appeal of the website than those from alternative conditions. The information quality levels were higher for those participants that recently had visualized the browsing conditions, what is explained due the fact that without having any task, like in all browsing conditions, information available were sufficient for participant's sense of understanding, what did not happen. Similar phenomenon occurred for information acquisition levels.

4.5 Experiment 2

4.5.1 Method

The second experiment of this article uses the same participants and replicates the design and stimuli of Experiment 1 but collecting and analyzing measures for different dependent variables (biological measures) via an eye-tracking analysis.

4.5.1.1 Participants

Besides participant's information provided in the last experiment, it should be mentioned that participants should not had any of the following conditions to be able to participate in this part of data collection: a) needing glasses to view websites – the eye-tracker works by firing infrared light pulses on the eye and captures the reflection off the cornea and the pupil with a sensor, so as to infer the direction of the gaze; this is known as the Pupil Centre Corneal Reflection (PCCR) technique. Glasses can obstruct the eye-tracker's reading of the corneal reflection, rendering it inaccurate; b) having a neurological diagnosis - in view of the above mentioned flashing infrared pulses from the eye-tracker, it is possible that certain neurological conditions may be exacerbated by it.

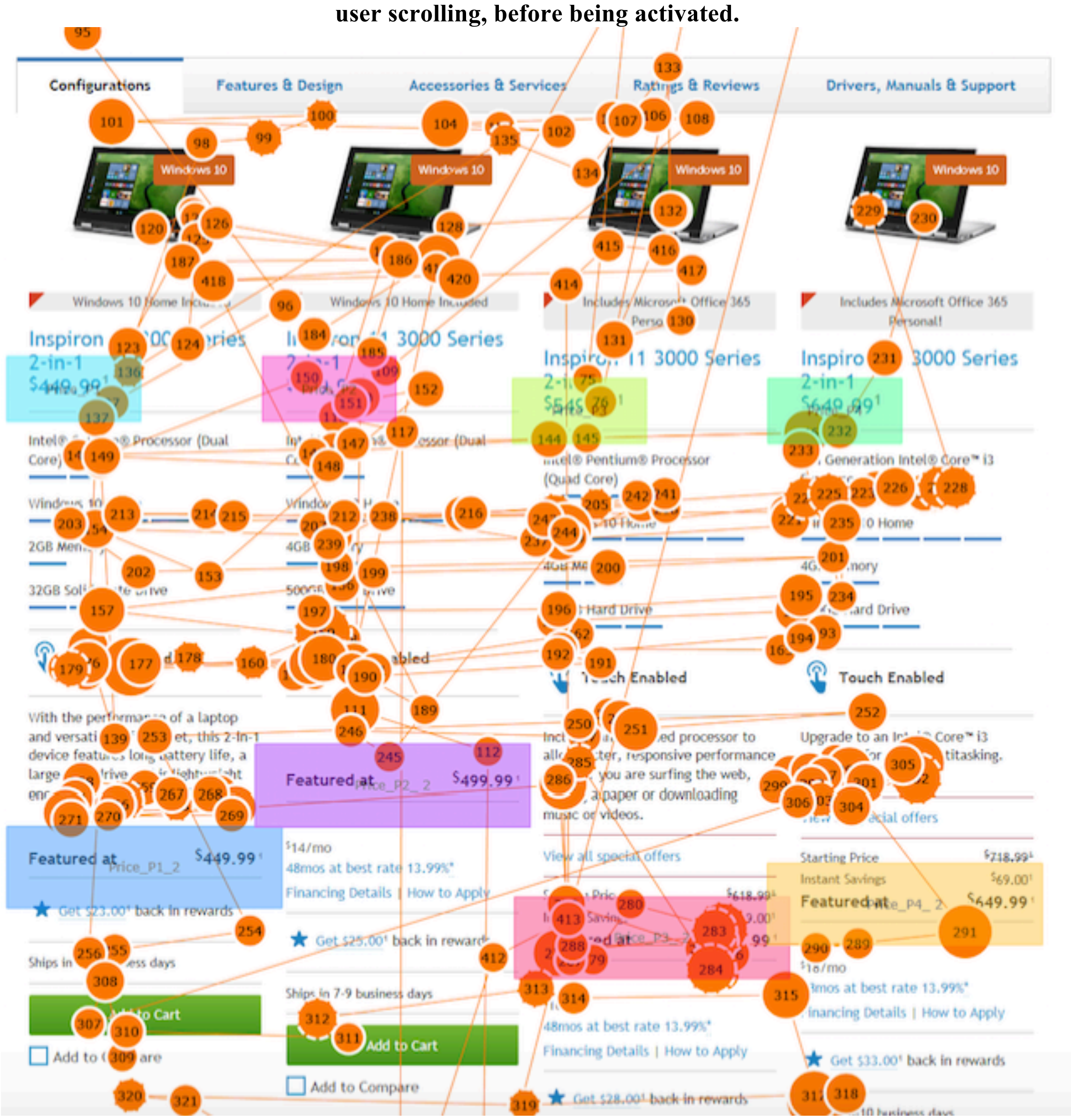
4.5.1.2 Eye-Tracking - Areas of Interest Coding

Areas of interest (AOIs) are defined as "rectangular regions of interest that represent units of information in the visual field" (Salvucci & Goldberg, 2000, p. 75). These AOIs use a duration threshold to distinguish fixations from passing saccades within the defined region, which was parameterized at a minimum of 100 milliseconds in this experiment. This parameterization is in line with the assertion that fixations are "rarely less than 100 milliseconds and most often in the range of 200-400 milliseconds" (Salvucci & Goldberg, 2000, p. 72).

The AOIs in this study were coded onto both static and dynamic recordings of participants using Tobii Studio software (Tobii Technology AB, Danderyd, Sweden). This was in response to the fact that Tobii studio was not able to make static images of all the pages on the websites, due to a large number of flash elements being present (Figure 17). To select what part of the websites each AOIs would be marked, we followed the critical information when buying (or considering to) a computer by Consumer Reports (2015), namely: a) accessories, b) configurations, c) features and design, d) price, and e) ratings and reviews.

Dynamic AOIs were used to capture eye-movement data. Since all AOIs on a dynamic recording must be present throughout the recording, when participants visited different parts of a webpage, certain AOIs had to be activated while others were deactivated. This was done so that only AOIs relevant to the current page viewed would capture eye-movements.

Figure 17 - Illustration of dynamic AOI activation process; AOIs are resized and repositioned, to match user scrolling, before being activated.



Obs.: Each circle in the image above represent a fixation and each line a saccadic movement.

Source: Research Data

To ensure AOIs captured all of the necessary elements of information seeking activities, various classes of AOIs were coded for each specific region. For example, to capture all information about "price", different AOIs were created where price information were present in the same webpage. Classes were created for each critical element suggested by Consumer Reports and then grouped into the overarching for later data export from the application. It is important to note that although the AOI classification scheme was made as suggested by Consumer Reports, there were plenty of meetings with the lab research team and professors to discuss and approve the use of this AOI coding. These discussions allowed for the validation of the steps taken in coding the AOIs and ensured the uniformity of the classes assigned.

Figure 18 – View of a Heat Map and some AOIs used in this study.

Source: Research Data

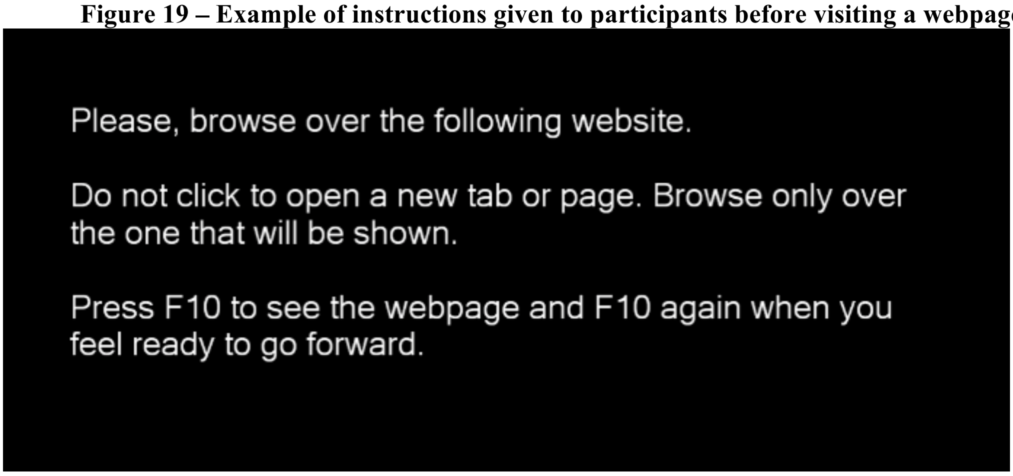
In the Figure 18, some of the AOIs used in this study can be seeing along with a Heat Map example. The rectangular colored areas are the AOIs, while the others are the indication of where this participant, for example, pay more attention to. This measure is extracted from a combination of number and duration of fixations.

4.5.1.3 Eye-Tracking - Tools for data collection and analysis

The primary instrument used for data collection was the Tobii X60 eye-tracker (Tobii Technology AB, Danderyd, Sweden), which recorded participant eye-movements throughout the experiment. Additionally, the Tobii Studio software was used to store the tracking data. Before the start of each experiment, the eye-tracker was calibrated for each participant to ensure the most accurate readings possible.

Tobii Studio was used to design the sequence of sites each participant would visit, as well as to direct participants to Qualtrics data collection after each stimulus. A total of 4 different sequences with a randomized website order were parameterized in the application. Once the experiment was initiated, users visited each site via Internet Explorer, which displayed automatically with the preset website from the sequence selected in Tobii Studio. In between each visit a black screen was displayed with white text indicating instructions for the next visit (Figure 19). Data were then exported from Tobii Software to R Studio, where they were cleaned and analyzed.

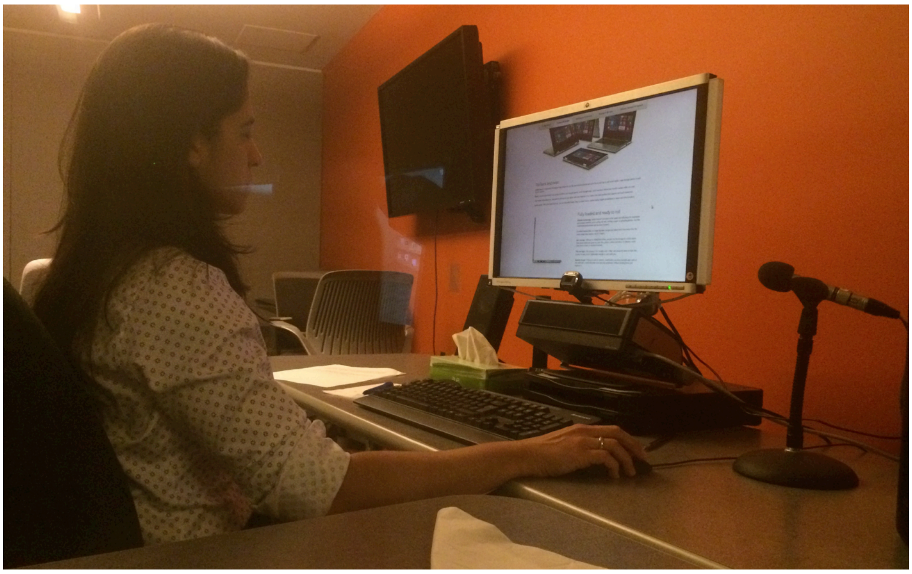
Figure 19 – Example of instructions given to participants before visiting a webpage.



4.5.1.4 Procedure

Participants were welcomed individually, by appointment, at the laboratory (Figure 20). They were exposed to four different conditions assigned randomly within subjects. After all initial procedures (acceptance term, calibration of equipment…), participants were asked to participate in an academic research and to follow the instructions on the screen. Participants had no more than 4 minutes to visit each of the webpages, time considered sufficient accordingly to pretests. If they feel confortable to advance to next step of the experiment they would press "F10" and they would be directed to the next task. If the 4 minutes were reached, system automatically advances to the next step. Thereafter, demographic, realism of the scenario and manipulation check questions were collected. Finally, the debriefing was held and participants received the monetary compensation along with a final consent informing the end of the study and that monetary compensation was properly delivered. The whole experiment took about 40 minutes to each participant.

Figure 20 - Research Assistant pretesting the experiment



Obs.: Photo taken from the other side of the two-way mirror experimentation room.

4.5.1.5 Measures

This study used two different types of measurements: a manipulation check measure, used to verify the effectiveness of the manipulation of the independent variables, as well as in the first experiment; and the biological dependent variables measures, i.e., Time to First Fixation.

4.5.1.5.1 Manipulation Check

For the manipulation check, it was questioned to the participant, at the end of the experiment, if information was presented to them in different ways of visualization. According to the data, everyone confirmed data were presented differently, however, when asked the aim of this research none of them got the right answer.

4.5.1.5.2 Dependent Variables

Time to First Fixation (seconds). This metric measures how long it takes before a test participant fixates on an active AOI or AOI group for the first time. The time measurement starts when the media containing the AOI is first displayed. For AOI groups, the time measurement starts when any of the media containing an AOI member of the group is first displayed. The AOIs do not have to be active for the time measurement to start. Time measurement stops when the participant fixates on the AOI if the AOI is active. For AOI groups, the time measurement stops when the participant fixates on any of the active AOIs belonging to the group. If during the recording the same media is displayed several times, with other media in between, the Time to First Fixation value will be calculated by adding each recorded media time of the media containing the AOI until the participant fixates on the active AOI. Recording time of media not containing the AOI is excluded from the calculations.

First Fixation Duration (seconds). This metric measures the duration of the first fixation on an AOI or an AOI group. When using AOI groups, the measured fixation corresponds to the first fixation on any of the AOIs belonging to the group. If at the end of the recording, the participant has not fixated on the AOI, the First Fixation Duration value will not be computed and that participant will thus not be included in the descriptive statistics calculations (e.g. when computing N).

Fixation Duration (seconds). This metric was previously called Fixation Length in older versions of Tobii Studio and measures the duration of each individual fixation within an AOI (or within all AOIs belonging to an AOI group). The N value used to calculate the descriptive statistics, such as mean and standard deviation, is based on the number of fixations. If during the recording, the participant returns to the same media element, the new fixations on the media will also be included in the calculations of the metric. If at the end of the recording, the participant has not fixated on the

AOI, the Fixation Duration value will not be computed and that recording will thus not be included in the descriptive statistics calculations (e.g. when computing averages for participant groups).

Total Fixation Duration (seconds). This metric measures the sum of the duration for all fixations within an AOI (or within all AOIs belonging to an AOI group), thus the N value used to calculate descriptive statistics is based on the number of recordings. If at the end of the recording, the participant has not fixated on the AOI, the Total Fixation Duration will not be computed and the recording will not be included in the descriptive statistics calculations (e.g. when computing N and means).

Fixation Count. This metric measures the number of times the participant fixates on an AOI or an AOI group. If during the recording the participant leaves and returns to the same media element, then the new fixations on the media will be included in the calculations of the metric. If at the end of the recording the participant has not fixated on the AOI, the Fixation Count value will not be computed and the recording will not be included in the descriptive statistics calculations (e.g. when computing N).

Total Visitation Duration (seconds). This metric measures the duration of all visits within an active AOI (or AOI group). In this case the N value used to calculate descriptive statistics is based on the number of recordings. Total Visit Duration is defined as the sum of visit durations of an active AOI (or AOI group). An individual visit is defined as the time interval between the first fixation on the active AOI and the end of the last fixation within the same active AOI where there have been no fixations outside the AOI. For AOI groups, an individual visit is defined as the time interval between the first fixation on any active AOI belonging to the group and the end of the last fixation within on any active AOI within the AOI group, where there have been no fixations outside the active AOIs of the AOI group. If at the end of the recording the participant has not fixated on the AOI, the Total Visit Duration value will not be computed and the recording will not be included in the descriptive statistics calculations (e.g. when computing N).

Visitation Count. This metric measures the number of visits within an active AOI (or AOI group). A visit is defined as the time interval between the first fixation on the active AOI and the end of the last fixation within the same active AOI where there have been no fixations outside the AOI. For AOI groups, a visit is defined as the time interval between the first fixation on any active AOI belonging to the group and the end of the last fixation within on any active AOI within the AOI group, where there have been no fixations outside the active AOIs of the AOI group. If at the end of the recording the participant has not fixated on the AOI, the Visit Count value will not be computed and the recording will not be included in the descriptive statistics calculations (e.g. when computing N).

4.5.2 Results

In order to examine if Depth-of-Field and Type of Search would be responsible for creating a difference in means on our dependent variables (Time to First Fixation, First Fixation Duration, Fixation Duration, Total Fixation Duration, Fixation Count, Total Visit Duration and Visitation Count), we performed several One-way Repeated Measures ANOVA.

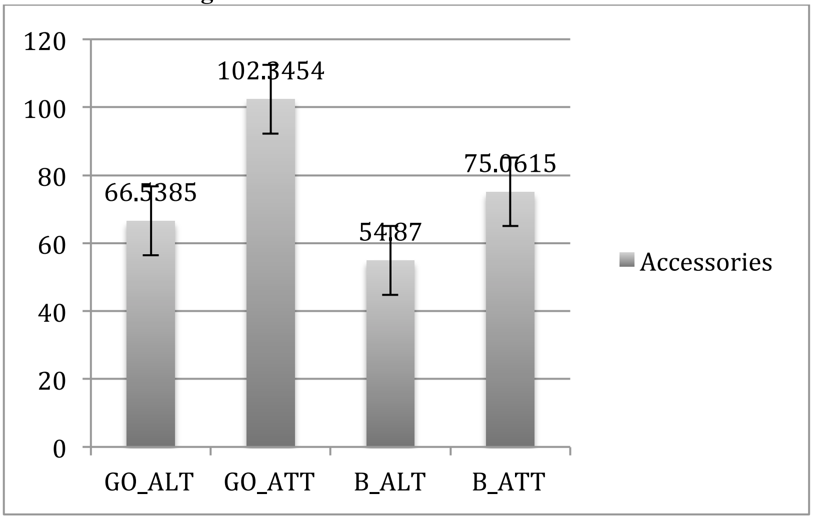
We present and analyze the results of this experiment in two parts. Firstly, we analyze if there is an impact of our conditions (GO_ALT, GO_ATT, B_ALT, B_ATT) in each of our dependent variables, splitting these findings for each of the AOIs (Accessories, Configuration, Features & Design, Price, and Ratings & Reviews). After, we present and analyze for each of our experimental conditions, if there is a difference in the total fixation duration for each of the AOIs.

4.5.2.1 Part I

In this section we report and analyze these data, except for those variables, which we did not find any statistic significance (First Fixation Duration, Total Visit Duration and Visitation Count).

Time to First Fixation. A repeated measures ANOVA determined the means for **Accessories** AOIs differed statistically significantly between conditions ($F(3, 36) = 7.147$, $p = 0.001$). Post hoc tests using the Bonferroni test revealed that the time to first fixation differed statistically significantly in some conditions. When viewing products by alternative, after a browsing task, B_ALT ($M = 54.87$, $SD = 18.11$), participants differed in time to first fixation from those situations where they were viewing products after a goal-oriented task, by attribute, GO_ATT ($M = 102.34$, $SD = 28.57$, $p = 0.001$) and from those situations where viewing products by attribute, after a browsing task, B_ATT ($M = 75.06$, $SD = 11.67$, $p = 0.047$). Figure 21 represents the effects of the factor on the time to first fixation.

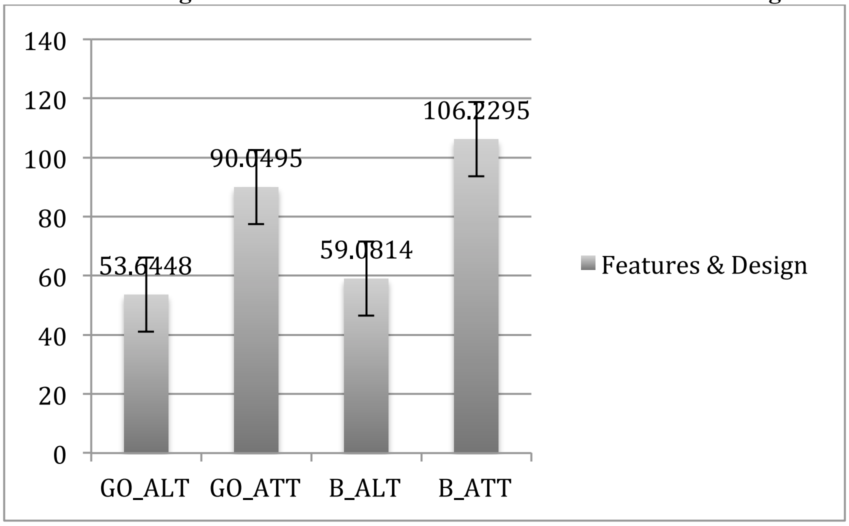
Figure 21 - Time to First Fixation for Accessories



(Error bars indicate ±1 standard error of the mean.)

A repeated measures ANOVA with a Greenhouse-Geisser correction determined the means for this **Features & Design** AOIs differed statistically significantly between conditions ($F(3, 60) = 3.598$, $p = 0.019$). Post hoc tests using the Bonferroni correction revealed that the time to first fixation differed statistically significantly in some conditions. After a browsing task, participants viewing products by alternative, B_ALT (M = 59.08, SD = 33.87), differed in time to first fixation from those situations where they were viewing products by attribute, B_ATT (M = 106.23, SD = 48.91, p = 0.001). In the same way after a goal-oriented task, participants viewing products by alternative, GO_ALT (M = 53.64, SD = 11.76), differed in time to first fixation from those situations where they were viewing products by attribute, GO_ATT (M = 90.05, SD = 22.98, p = 0.003). Figure 22 represents the effects of the factor on the time for first fixation.

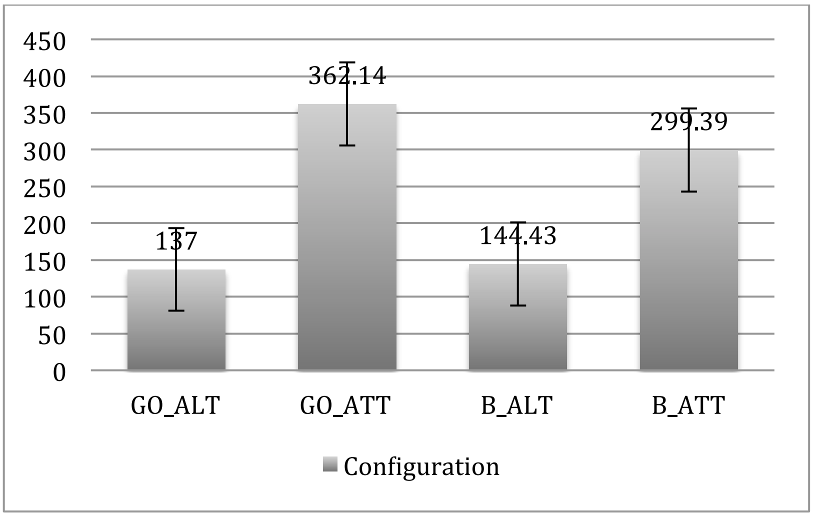
Figure 22 - Time to First Fixation for Features & Design



(Error bars indicate ±1 standard error of the mean.)

Fixation Duration. A repeated measures ANOVA with a Greenhouse-Geisser correction determined that means for **Configuration** differed statistically significantly between conditions ($F(2.324, 62.74) = 29.64$, $p < 0.001$). Post hoc tests using the Bonferroni correction revealed that the fixation duration differed statistically significantly in some conditions. When viewing products by alternative, after a browsing task, B_ALT (M = 144.43, SD = 46.18), participants differed in time of fixation duration from those situations where they were viewing products after a goal-oriented task, even by attribute, GO_ATT (M = 362.14, SD = 178.67, p < 0.001) or when just browsing, B_ATT (M = 299.39, SD = 103.59, p < 0.001). We also found difference in means between the GO_ALT (M = 137, SD = 53.50) and GO_ATT, B_ATT at p < 0.001 levels. (Figure 23).

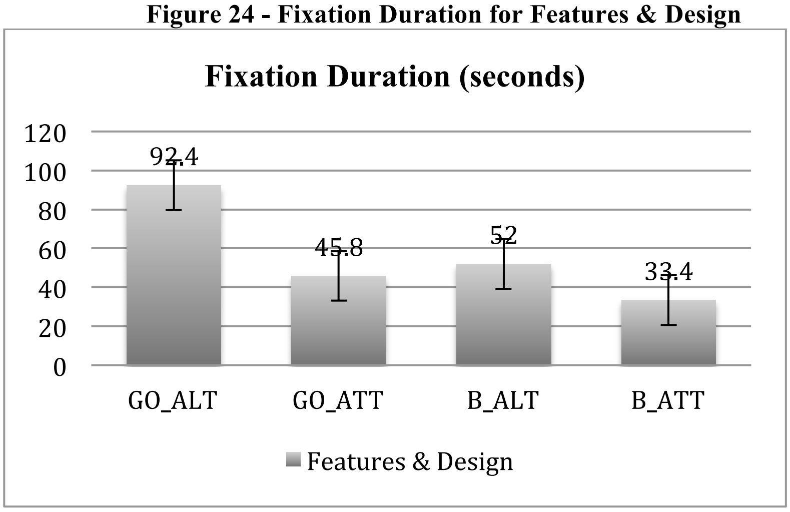
Figure 23 - Fixation Duration for Configurations



(Error bars indicate ±1 standard error of the mean.)

A repeated measures ANOVA determined the means for **Features & Design** AOIs differed statistically significantly between conditions (F(3, 57) = 6.29, p = 0.001). Post hoc tests using the Bonferroni test revealed the fixation duration differed statistically significantly in some conditions. When viewing products by alternative, after a goal-oriented task, GO_ALT (M = 92.4, SD = 28.47), participants differed in fixation duration from those situations where they were viewing products after a browsing task, either by attribute, B_ATT (M = 33.4, SD = 11.8, p = 0.02) or by alternative, B_ALT (M = 52, SD = 16.8, p = 0.025). Figure 24 represents the effects of the factor on the time to first fixation.

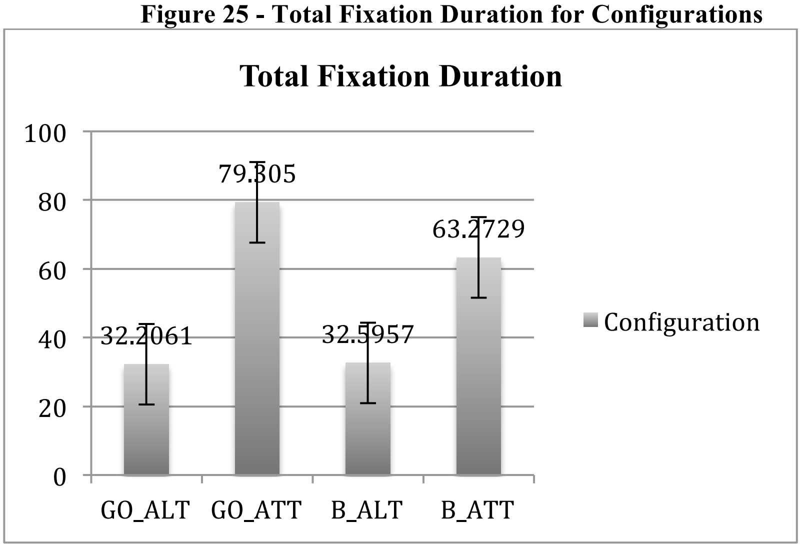
Figure 24 - Fixation Duration for Features & Design



(Error bars indicate ±1 standard error of the mean.)

Total Fixation Duration. A repeated measures ANOVA with a Greenhouse-Geisser correction determined that means for **Configuration** (Figure 25) differed statistically significantly between conditions ($F(2.443, 65.96) = 24.65$, $p < 0.001$). Post hoc tests using the Bonferroni correction revealed that the fixation duration differed statistically significantly in some conditions. When viewing products by attribute, after a goal oriented task, GO_ATT (M = 79.30, SD = 26.86), participants differed in total fixation duration from those situations where they were viewing products by alternative, even after a goal-oriented task, GO_ALT (M = 32.30, SD = 11.35, p < 0.001) or after browsing, B_ALT (M = 32.60, SD = 12.42, p < 0.001). We also found difference in means between the B_ATT (M = 63.27, SD = 13.12) and GO_ALT, B_ALT at p < 0.003 levels.

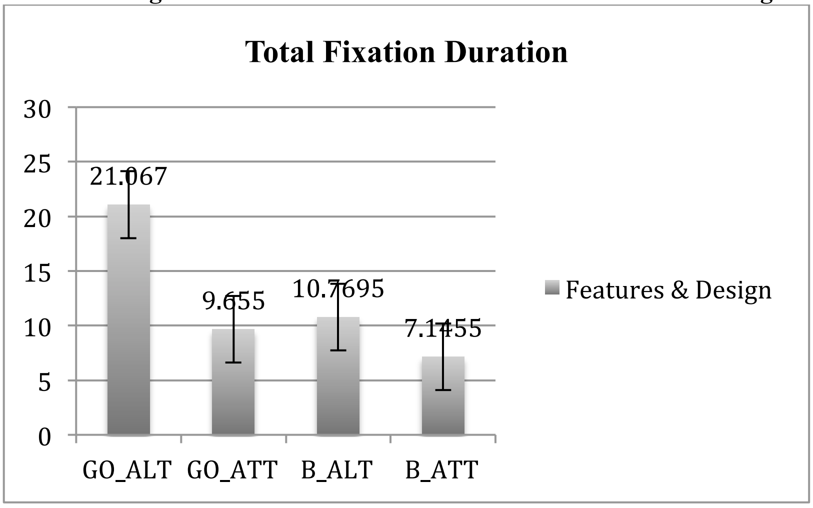
Figure 25 - Total Fixation Duration for Configurations



(Error bars indicate ±1 standard error of the mean.)

A repeated measures ANOVA determined the means for **Features & Design** (Figure 26) AOIs differed statistically significantly between conditions ($F(3, 57) = 7.38$, $p = 0.001$). Post hoc tests using the Bonferroni test revealed the total fixation duration differed statistically significantly in some conditions. When viewing products by alternative, after a goal-oriented task, GO_ALT (M = 21.07, SD = 7.89), participants differed in total fixation duration from all other situations like, GO_ATT (M = 9.65, SD = 2.12, p = 0.037), B_ALT (M = 10.77, SD = 3.57, p = 0.017) and B_ATT (M = 7.14, SD = 2.71, p = 0.011).

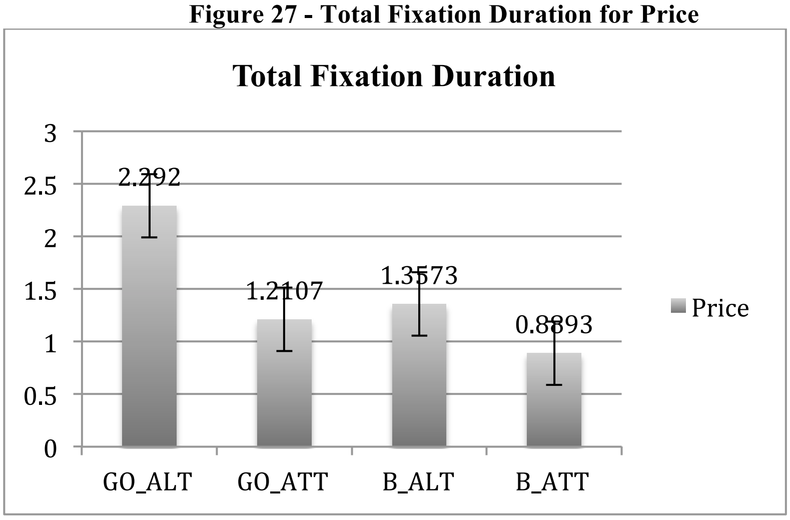
Figure 26 - Total Fixation Duration for Features & Design



(Error bars indicate ±1 standard error of the mean.)

A repeated measures ANOVA with a Greenhouse-Geisser correction determined that means for **Price** (Figure 27) differed statistically significantly between conditions (F(2.069, 28.97) = 4.3, *p* = 0.022). Post hoc tests using the Bonferroni correction revealed that total fixation duration differed statistically significantly only when viewing products by attribute, after a browsing task, B_ATT (M = 0.89, SD = 0.22) versus when were viewing products after a goal-oriented task by alternative, GO_ALT (M = 2.29, SD = 0.86, p = 0.021).

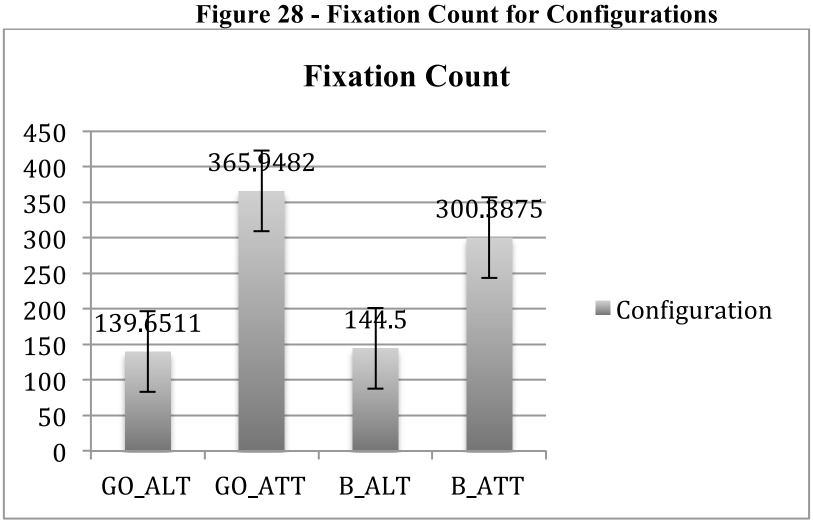
Figure 27 - Total Fixation Duration for Price



(Error bars indicate ±1 standard error of the mean.)

Fixation Count. A repeated measures ANOVA with a Greenhouse-Geisser correction determined that means for **Configuration** differed statistically significantly between conditions ($F(2.323, 62.72) = 30.36$, $p < 0.001$). Post hoc tests using the Bonferroni correction revealed that the fixation duration differed statistically significantly in some conditions. When viewing products by alternative, after a browsing task, B_ALT (M = 144.5, SD = 36.11), participants differed in fixation count from those situations where they were viewing products by attribute, even after a goal-oriented task, GO_ATT (M = 365.95, SD = 142.73, p < 0.001) or after a browsing task, B_ATT (M = 300.39, SD = 102.14, p < 0.001). We also found difference in means between the GO_ALT (M = 139.65, SD = 50.5) and GO_ATT, B_ATT at p < 0.001 levels. (See Figure 28).

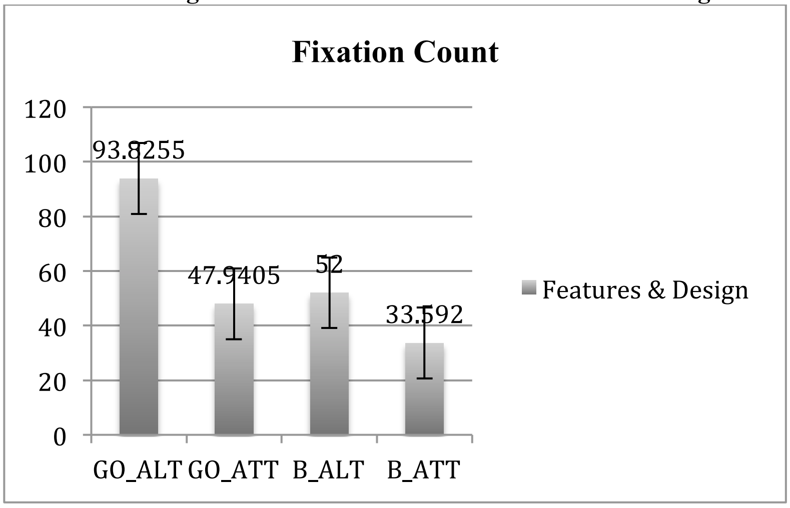
Figure 28 - Fixation Count for Configurations



(Error bars indicate ±1 standard error of the mean.)

A repeated measures ANOVA determined the means for **Features & Design** (Figure 29) AOIs differed statistically significantly between conditions ($F(3, 57) = 6.46$, $p = 0.001$). Post hoc tests using the Bonferroni test revealed the fixation count differed statistically significantly in some conditions. When viewing products by alternative, after a goal-oriented task, GO_ALT (M = 93.82, SD = 36.74), participants differed in fixation count from those situations where they were viewing products after a browsing task, either by attribute, B_ATT (M = 33.59, SD = 15.62, p = 0.016) or by alternative, B_ALT (M = 52, SD = 16.80, p = 0.017). Figure 29 represents the effects of the factor on the time to first fixation.

Figure 29 - Fixation Count for Features & Design



(Error bars indicate ±1 standard error of the mean.)

We did not found difference in means for "price" and "ratings and reviews" at $p < 0.05$ levels.

4.5.2.2 Part II

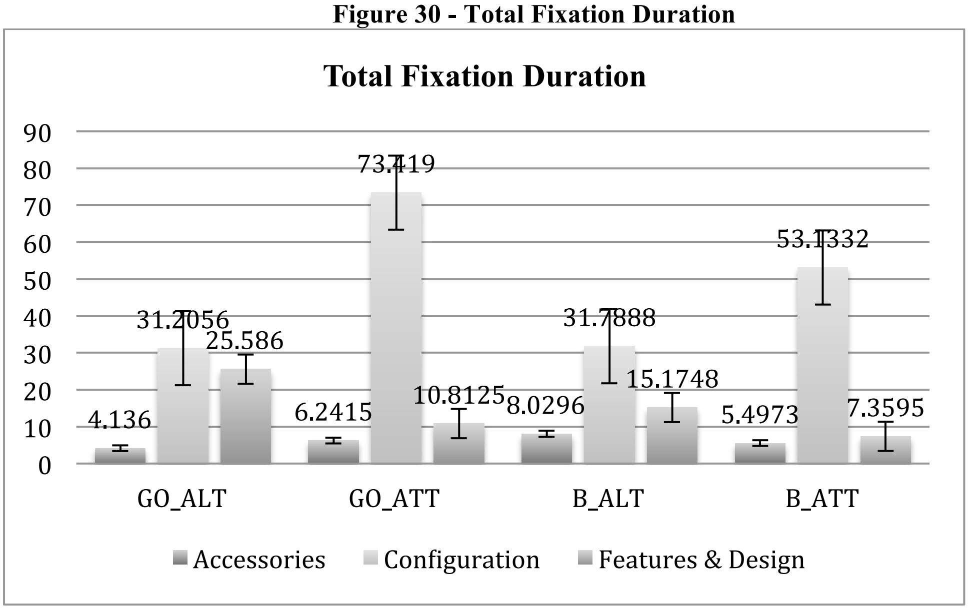
Total Fixation Duration. A repeated measures ANOVA determined the participants pay more attention to some AOIs in spite of others, within the same condition. For the GO_ALT condition ($F(2,48) = 19.92$, $p < 0.001$), participants attention to Accessories ($M = 4.14$, $SD = 1.87$) differed statistically significantly from the attention spent to Configuration ($M = 31.20$, $SD = 8.75$, $p < 0.001$) and to Features & Design ($M = 25.58$, $SD = 6.91$, $p < 0.001$). For the GO_ATT condition ($F(1.051,19,97) = 38.39$, $p < 0.001$), participants attention to Configuration ($M = 73.42$, $SD = 16.28$) differed statistically significantly from the attention spent to Accessories ($M = 6.24$, $SD = 1.44$, $p < 0.001$) and to Features & Design ($M = 10.81$, $SD = 2.54$, $p < 0.001$). For the B_ALT condition ($F(1.324, 31.76) = 16.36$, $p < 0.001$), participants attention to Accessories ($M = 8.03$, $SD = 2.22$) differed statistically significantly from the attention spent to Configuration ($M = 31.79$, $SD = 9.79$, $p < 0.001$) and to Features & Design ($M = 15.17$, $SD = 3.48$, $p = 0.017$). Also, attention to Configuration and Features & Design differed at $p = 0.005$ levels. Finally, for the B_ATT condition ($F(1.022, 21.47) = 27.18$, $p < 0.001$), participants attention to Configuration ($M = 53.13$, $SD = 11.73$) differed statistically significantly from the attention spent to Accessories ($M = 5.5$, $SD = 1.51$, $p < 0.001$) and to Features & Design ($M = 7.35$, $SD = 2.5$, $p < 0.001$).

Table 8 - Descriptive for Total Fixation Duration

Factors		GO_ALT	GO_ATT	B_ALT	B_ATT
Accessories	**Mean**	**4.136**	**6.2415**	**8.0296**	**5.4973**
	SD	1.8768	1.44408	2.22242	1.51961
Configuration	**Mean**	**31.2056**	**73.419**	**31.7888**	**53.1332**
	SD	8.75499	16.28444	9.79497	11.73717
Features & Design	**Mean**	**25.586**	**10.8125**	**15.1748**	**7.3595**
	SD	6.91143	2.54981	3.48983	2.50508

Source: Research Data

Figure 30 - Total Fixation Duration



(Error bars indicate ±1 standard error of the mean.)

4.5.3 Discussion

In this experiment we expand the findings of the previous study by including some biological outcomes from an eye-tracking technique. In studying information search and information processing, eye-tracking has proven to be an excellent process-tracing method as it is an unobtrusive technology that does not distract users from the task at hand as data on eye movements can be collected without the user being aware of it. Furthermore, eye tracking offers a rich data set, in terms of user behavior in an online context, by being able to pinpoint the exact location of fixations on the display as well as the saccades between these fixations.

Eye tracking was used to monitor how individuals search for information. To characterize the search pattern, we established AOIs for each important characteristic of the product. This, in combination with our stimuli regarding both of independent variables allow us to analyze to each situation people pay more attention to.

The results of this study also led to important findings. The most interesting findings of the present study are that it is possible to predict how product information will be processed by consumers. The eye-movement data showed that there are statistically significant differences in visual attention between groups for the overall data and for specific analysis.

For instance, we found the time for first fixation was lower when participants were exposed to conditions where only one product was presented at a time (alternative) in spite of those situations where participants were navigating through the attribute conditions (when more than one product were presented at a time). We found the same tendency when analyzing the duration of those fixations. However, the total fixation duration this tendency was confirmed only in the AOIs containing the configurations of the products. In the others AOIs, such as price, we found the opposite effect, the total fixation duration were higher for situations containing products displayed by alternative.

In the overall, we found consumers spend more time looking at information containing products' configuration such as processor or memory, in spite of other AOIs like accessories and features & design. This phenomenon occurred for all experimental conditions, what makes us to confirm this tendency as a general pattern of search for information in this kind online store. When differentiating alternative versus attribute conditions, one important evidence was found regarding the features AOIs. Consumers exposed to alternative conditions pay more attention to this kind of information than those exposed to attribute conditions, when compared to others AOIs.

4.6 General Discussion

This article aimed to contribute to online information seeking literature by investigating participant's online search and browse behaviors and the resulting processing of information when viewing products presented visually differently in a webpage. These patterns of individual's visualization have important practical implications for website design, creating experiences that supports the type of information search undertaken by consumers.

In view of this, recall the objectives of the present article were three-fold. The first was to better understand the relation between depth-of-field and type of search on the information seeking behavior. The second, was to providing a broader, more comprehensive study on web navigation behavior, integrating website navigational characteristics, user characteristics, consumer responses, and outcomes (biological and behavioral). Finally, the third objective was to offer companies the key visual elements where individuals pay more attention during a visit to a product's webpage.

To achieve these objectives and as one of this paper's contributions, we employed a multi-method approach – a self-reported questionnaire and eye-movement data – to gain a deeper understanding of the data when observing a complex phenomenon, as consumers themselves may not be aware of their reactions in such situations. In line with our objectives, we performed two experiments, one measuring behavioral outcomes and the other one attempting to biological measures.

The first experiment examines the influence of type of search and depth of field in the consumer online information seeking behavior using behavioral measures. The results of the current study led to several important findings. Firstly, the intention to revisit the website is higher for those in the browser conditions when viewing products by alternative (one product at a time) than for any other condition. We explain this putting into consideration that in other conditions participants had a stipulated task, which was responsible for making them pay more attention in the website, or had more information about products (when comparing products at the "attribute" level). This, could led participants to further revisit the webpage to get more information about the product.

Also, the information quality levels were higher for those participants that recently had visualized the browsing conditions, what is explained due the fact that without having any task, like in all browsing conditions, information available were sufficient for participant's sense of understanding (van der Land et al., 2013), what did not happen. Similar phenomenon occurred for information acquisition levels.

In the second experiment we expand those findings by including some biological outcomes from an eye-tracking technique. In studying information search and information processing, eye-tracking has proven to be an excellent process-tracing method as it is an unobtrusive technology that does not distract users from the task at hand as data on eye movements can be collected without the user being aware of it. Furthermore, eye tracking offers a rich data set, in terms of user behavior in an online context, by being able to pinpoint the exact location of fixations on the display as well as the saccades between these fixations.

Eye tracking was used to monitor how individuals search for information. To characterize the search pattern, we established AOIs for each important characteristic of the product. This, in combination with our stimuli regarding both of independent variables allow us to analyze to which situation people pay more attention to.

The results of this study also led to important findings. The most interesting findings of the present study are that it is possible to predict how consumers will process product information, in accordance to Chernev (2003) and Ganapathy, Ranganathan, and Sankaranarayanan (2004). The eye-movement data showed that there are statistically significant differences in visual attention between groups for the overall data and for specific analysis.

For instance, we found the time for first fixation was lower when participants were exposed to conditions where only one product was presented at a time (alternative) in spite of those situations where participants were navigating through the attribute conditions (when more than one product were presented at a time). We found the same tendency when analyzing the duration of those fixations. However, the total fixation duration this tendency was confirmed only in the AOIs containing the configurations of the products. In the others AOIs, such as price, we found the opposite effect, the total fixation duration were higher for situations containing products displayed by alternative.

In the overall, we found consumers spend more time looking at information containing products' configuration such as processor or memory, in spite of other AOIs like accessories and features & design. This phenomenon occurred for all experimental conditions, what makes us to confirm this tendency as a general pattern of search for information in this kind online store. When differentiating alternative versus attribute conditions, one important evidence was found regarding the features AOIs. Consumers exposed to alternative conditions pay more attention to this kind of information than those exposed to attribute conditions, when compared to others AOIs.

For website designers, the ability to predict the type and how information is processed when viewing products based on eye-movements of users on webpages, opens the way for a better website customization. Website pages could be customized to best present the information in function of how the user has navigated the site, rendering the experience easier, more enjoyable and efficient. In this regard, a match between the shopping task and the information format has been shown to allow users to search the information space more efficiently (Hong, Thong, & Tam, 2004). Website designers should prepare several different presentations of result page information, in order to display the one that best fits the user's information seeking behavior, as discussed below.

Nonetheless, this research has limitations like the use of a sample of university students in its majority, which may not be representative of the general population. Future researchers could use a broader sample and implement experiments to analyze the message area of the screen for detailed product descriptions, resulting in additional insights and generalized experimental results.

As another idea for future researches in this topic, we recommend the use of some of our dependent variables in the second study, such as time to first fixation or fixation duration as independents variables in further studies. For instance, in doing that, one could evaluate if a group of consumers which had more (less) fixations count than other is likely to have a higher (lower) intention to revisit the website.

Finally, it should be noted that the device used for participants' interaction with the websites was the desktop computer. Advances in technology over the last decade have seen an explosion of mobile devices used to access and search on the Internet. Subsequent studies could make use of a variety of different mobile devices from smartphones to tablets so as to investigate whether or not the type of devices used to interact with websites have an effect on the breadth and depth of information search and processing activities.

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CHAPTER 5

Synthesis, Conclusion and Future Researches

The objective of this dissertation was to investigate and measure the effects of different visual representations of products on individual's behavior during pre-purchase online information seeking activities. More specifically, this dissertation analyzed what type of information customers considered most important and pays more attention and what is the extent of the visual aspect and its impact in information seeking behavior. To do so, five experiments were conducted, three using online participants via Amazon Mechanical Turk, and two using participants in a laboratory setting, being collected biological measures in one of them.

<u>The first essay</u>, discuss that online consumer information search became a crucial initial step in the purchase decision process. Through two studies, the essay shows how different degrees of evaluability of the same online review can influence on helpfulness, overestimation of information and purchase intention. It also evidence individual's involvement while browsing has a moderating role in the relation between evaluability and helpfulness as well as in the relation between evaluability and purchase intention.

Empirically, analyzing the first experiment it was found that different ways of presentation of the same online review influence not only the purchase intention, but also how helpful consumers perceive that information to make a decision and how they overestimate one or other kind of information depending on the information presentation. We can assume people exposed to the graphic review are too much disposed to buy the product than people exposed to the textual condition, and people presented to textual and graphic reviews consider the information more helpful than those presented to reviews containing both presentations. Also, consumers overestimate one or other kind of information depending on how this information is presented.

Regarding the second experiment, we found the interaction between evaluability and involvement has a significant effect on purchase intention proposing involvement moderates the relationship between evaluability and purchase intention. We also observed a significant impact of the interaction between evaluability and involvement on helpfulness. This interaction between evaluability and involvement has a significant effect on helpfulness proving that involvement moderates the relationship between evaluability and helpfulness. For the variable overestimation of Information, the interactions between evaluability and involvement was not statistically significant showing that involvement does not moderates the relationship between evaluability and overestimation of information.

Regarding cognitive fit (CFT) and cognitive load theories (CLT), CFT say when a data format fits for its use, more effective and efficient problem-solving performance is achieved. We found similar results in this research, once when information provided to costumers were presented in a graphic condition, we found better levels of helpfulness and overestimation of information. However, when we presented the condition which both visual elements were presented (graphic and textual information) some of these measures were even better, which may led into what CLT poses when saying different kinds of information presentation, at the same time, reduces the cognitive load and leveraging performance. Through this article we could follow Lurie and Swaminathan (2009) suggestion in analyzing the potential moderating role that involvement may play because many visualization tools require consumer/user effort. We found that this moderating role, at least to date, occurs only for purchase intention and helpfulness when analyzing evaluability. This expands the findings from Schmutz, Heinz, Métrailler, & Opwis (2009) and collaborates to authors suggestions of using this variable as moderator it affect the way in which consumers seek out information on a particular site.

The managerial contribution of this article addresses mainly in the fact online retailers can take advantage of these findings when developing their web interfaces or e-commerce strategies. Slightly differences in the configuration of the online reviews section of the websites, like presenting the reviews using a textual or tabular layout, can bring important differences in terms of perception of the website from consumers and, also, increasing costumer's purchase intention.

The second essay, aimed to analyze the relationship between depth-of-field and type of search on several behavioral outcomes, such as intention do revisit the website and visual appeal. It was also investigated whether or not involvement, expertise and attitude toward products moderates these relations.

Analyzing the experiment (the third in the overall dissertation) we found that different ways of presentation of the product online can influence outcomes such as the intention to revisit the website, websites' visual appeal and individual information acquisition. From a theoretical perspective, we can assume people exposed to conditions where products were presented by attribute have a higher intention to revisit the website, as well as have a higher perception of the websites' visual appeal. However, this relation is the opposite when analyzing the individual information acquisition while visiting the website, once people exposed to the conditions where products were presented by alternative had higher scores for this variable.

A significant main effect was found only for depth-of-field on intention to revisit, information acquisition, and visual appeal. The effect of type of search was not significant for intention to revisit, information acquisition and visual appeal and there was no evidence of a significant interaction. These results suggest that the significant differences in means for intention to revisit, information acquisition and visual appeal were induced by depth-of-field, rather than by type of search manipulations. This result goes against those presented by Chernev (2003) that found differences in type of search, however, it must be said that context studies by the author was an offline context, in opposition to the online used in this dissertation.

The article also examined the possible moderating role of involvement, attitude toward product and expertise in linking de depth-of-field with our outcomes. It was found only significant moderation effects for involvement and attitude toward product for the relation between depth-of-field and intention to revisit. Participants with a higher level of involvement (and as high it gets) had higher intention to revisit the website, while for participants with a lower level of attitude toward product (and as low it gets), higher was the intention to revisit the website.

The managerial contribution of this article addresses mainly in the fact online retailers and web designers can take advantage of these findings when developing their web interfaces or e-commerce strategies. Differences in the configuration of the product's presentation in the websites, like presenting them side-by-side facilitating attribute comparison, can bring important differences in terms of perception of the website from consumers and, also, increasing costumer's intention to revisit the website.

Drawing on the findings of the first and second essays, the third essay focused on replicate the finding of the second article via biological measures using an eye-tracking devices. Also, attention variables were included in the model. The third article aimed to contribute to online information seeking literature by investigating participant's online search and browse behaviors and the resulting processing of information when viewing products presented visually differently in a webpage. These patterns of individual's visualization have important practical implications for website design, creating experiences that supports the type of information search undertaken by consumers.

To achieve the objectives of the last article it was employed a multi-method approach – a self-reported questionnaire and eye-movement data – to gain a deeper understanding of the data when observing a complex phenomenon, as consumers themselves may not be aware of their reactions in such situations. In line with our objectives, we performed two experiments, one measuring behavioral outcomes and the other one attempting to biological measures.

The first experiment of the article (the fourth in the overall) examined the influence of type of search and depth of field in the consumer online information seeking behavior using behavioral measures, similar to the article two, but using repeated-measures for conditions, within subjects. The results of this study led to several important findings. Firstly, the intention to revisit the website is higher for those in the browser conditions when viewing products by alternative (one product at a time) than for any other condition. We explain this putting into consideration that in other conditions participants had a stipulated task, which was responsible for making them pay more attention in the website, or had more information about products (when comparing products at the "attribute" level). This, could led participants to further revisit the webpage to get more information about the product.

Also, the information quality levels were higher for those participants that recently had visualized the browsing conditions, what is explained due the fact that without having any task, like in all browsing conditions, information available were sufficient for participant's sense of understanding (van der Land et al., 2013), what did not happen. Similar phenomenon occurred for information acquisition levels.

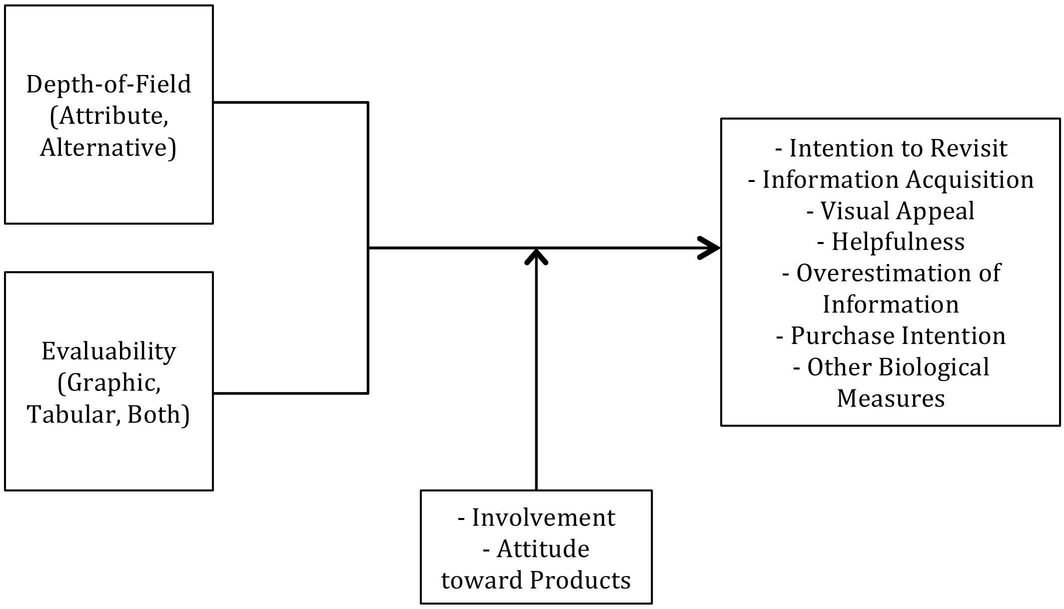
In the second experiment of the last article (the fifth in the overall) we expanded those findings by including some biological outcomes from an eye-tracking technique. The results of this study also led to important findings. The most interesting findings of the present study are that it is possible to predict how consumers will process product information, in accordance to Chernev (2003) and Ganapathy, Ranganathan, and Sankaranarayanan (2004) studies that used other variables. The eye-movement data showed that there are statistically significant differences in visual attention between groups for the overall data and for specific analysis.

For instance, we found the time for first fixation was lower when participants were exposed to conditions where only one product was presented at a time (alternative) in spite of those situations where participants were navigating through the attribute conditions (when more than one product were presented at a time). In the overall, we found consumers spend more time looking at information containing products' configuration such as processor or memory (in the case of computers), in spite of other AOIs like accessories and features & design. This phenomenon occurred for all experimental conditions, what makes us to confirm this tendency as a general pattern of search for information in this kind online store. When differentiating alternative versus attribute conditions, one important evidence was found regarding the features AOIs. Consumers exposed to alternative conditions pay more attention to this kind of information than those exposed to attribute conditions, when compared to others AOIs. These findings extends the research by Jia, Shiv and Rao (2014), once authors suggested the use of eye-tracking measures of visual attention to explore precise changes in visual scrutiny that may underlie different effects from visual characteristics.

For website designers, the ability to predict the type and how information is processed when viewing products based on eye-movements of users on webpages, opens the way for a better website customization. Website pages could be customized to best present the information in function of how the user has navigated the site, rendering the experience easier, more enjoyable and efficient. In this regard, a match between the shopping task and the information format has been shown to allow users to search the information space more efficiently (Hong, Thong, & Tam, 2004). Website designers should prepare several different presentations of result page information, in order to display the one that best fits the user's information seeking behavior, as discussed below.

Many research opportunities are open after the findings of this dissertation. Figure 31, exemplifies some of these opportunities.

Figure 31 - Proposed Model for Future Investigations



In this model, we try to consolidate, in a unique model, variables that were found to present statistically significance in our previous studies. The idea of bring this element in the end of this dissertation is due once all dissertation was developed under a common background, the pre-purchase online information search. Future empirical investigations can be conducted aiming to explore this model and broader the findings of this document.

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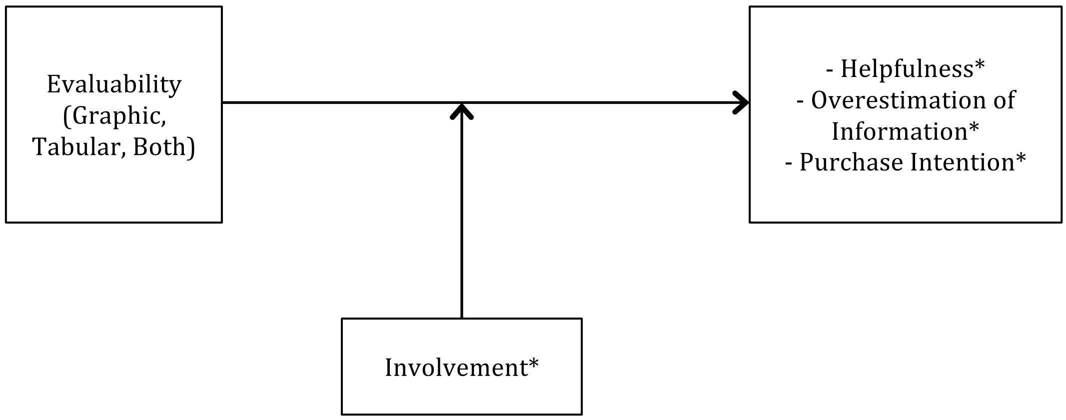
VAN DER LAND, S., SCHOUTEN, A., FELDBERG, F., HOOF, B., HUYSMAN, M. (2013). Lost in space? Cognitive fit and cognitive load in 3D virtual environments. **Computers in Human Behavior.** v. 29, p. 1054-1064.

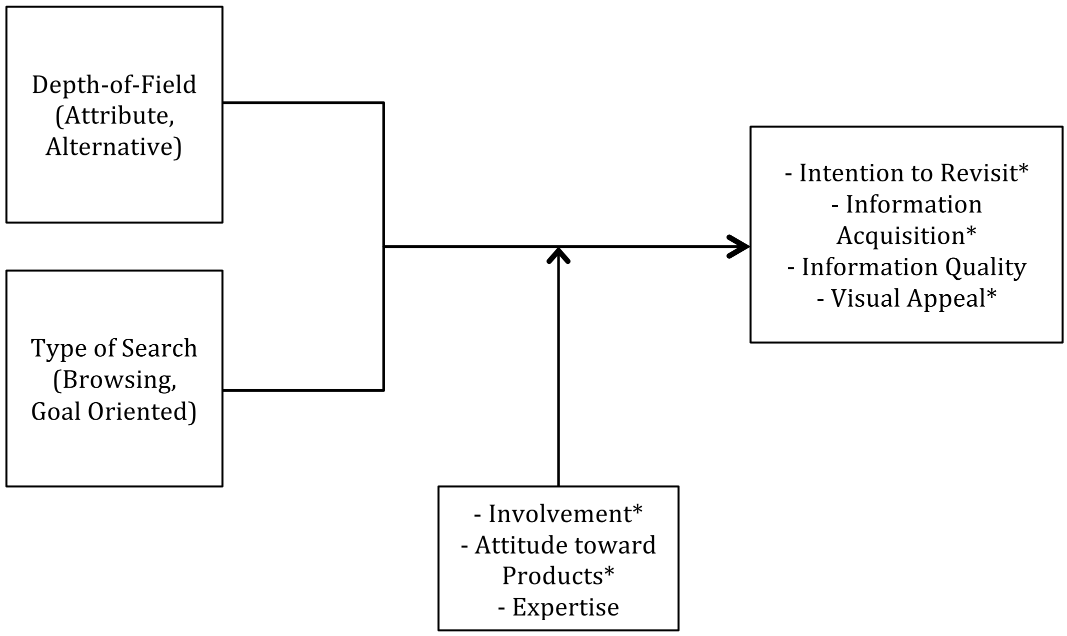
APPENDIX 1

Conceptual Model for Article 1. Note that (*) indicates a statistically significant relation at p < .05 levels.



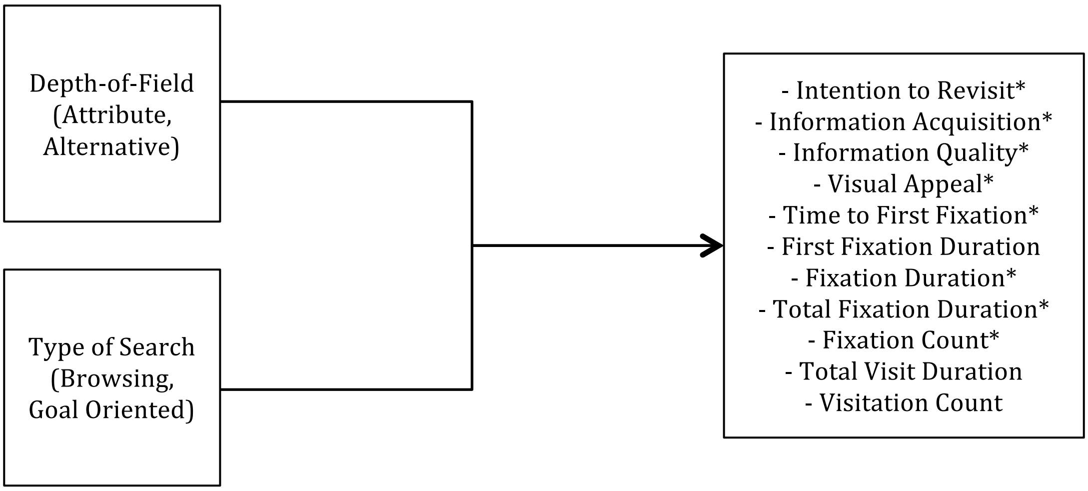
APPENDIX 2

Conceptual Model for Article 2. Note that (*) indicates a statistically significant relation at p < .05 levels.



APPENDIX 3

Conceptual Model for Article 3. Note that (*) indicates a statistically significant relation at p < .05 levels.



APPENDIX 4

FORMULAIRE DE CONSENTEMENT À UNE EXPÉRIMENTATION AU TECH³LAB

1. PRESENTATION DU PROJET DE RECHERCHE

Nous vous invitons à participer au projet de recherche portant sur la comparaison de produits en contexte de commerce électronique.

Ce projet est réalisé sous la supervision de Professeur Pierre-Majorique Léger que vous pouvez rejoindre par téléphone au 514-340-7013 ou par courriel à pml@hec.ca.

2. DESCRIPTION DE L'EXPERIMENTATION

Lors de cette expérience, il vous sera demandé de visitez la page web de certains produits de la firme Dell. S'il-vous-plaît, procédez à ces tâches de manière naturelle et détendue. Aucun jugement n'est porté sur vos réactions.

Veuillez noter que la firme Dell n'est partie prenante à cette étude. Les résultats de cette études ont uniquement pour but la publication scientifique.

3. DESCRIPTION DES OUTILS DE MESURE UTILISÉS DANS CETTE RECHERCHE

Durant l'expérience, vous devrez répondre à un questionnaire. S'il-vous-plaît, répondez à ces questions sans hésitation parce que, généralement, votre première impression reflète souvent le mieux votre véritable opinion. Il n'y a pas de limite de temps pour compléter ce questionnaire.

a) Collecte des données du mouvement des yeux (oculométrie)

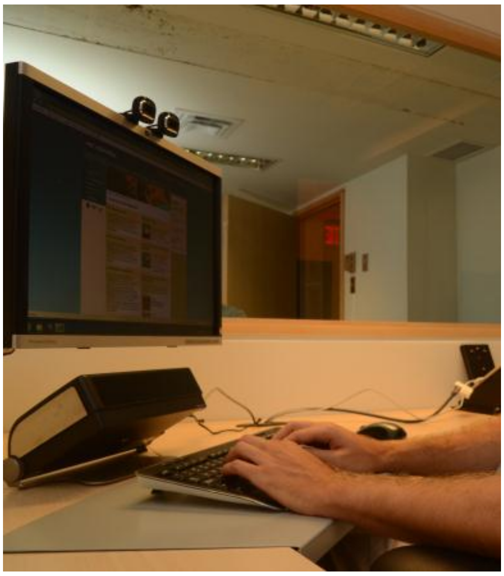
Aussi, nous allons collecter des données oculométriques lorsque que vous participerez à cette expérience. L'oculomètre utilise une caméra à lumière infrarouge pour calculer la direction de votre regard à l'écran. Au début de l'expérience, une courte calibration est requise; on vous demandera de fixer des points précis sur l'écran de l'ordinateur. L'utilisation de l'oculomètre est complètement non intrusive. La lumière infrarouge utilisée ne comporte aucun risque. **Vous avez le droit de refuser que l'oculomètre soit utilisé. Dans ce cas, vous ne pourrez pas participer à l'expérimentation.**

Votre participation à ce projet de recherche doit être totalement volontaire. Vous pouvez refuser de répondre à l'une ou à l'autre des questions. Il est aussi entendu que vous pouvez demander de mettre un terme à la rencontre, ce qui interdira au chercheur d'utiliser l'information recueillie. Pour toute question en matière d'éthique, vous pouvez communiquer avec le secrétariat du Comité d'éthique de la recherche (CER) de HEC Montréal par téléphone au 514 340-7182 ou par courriel à cer@hec.ca. N'hésitez pas à poser au chercheur toutes les questions que vous jugerez pertinentes.

4. POSITIONNEMENT DES SENSEURS

Les sections suivantes illustrent le positionnement des divers capteurs utilisés dans cette expérimentation

OCULOMÉTRIE



5. CONFIDENTIALITE DES DONNEES RECUEILLIES

Le chercheur, de même que tous les autres membres de l'équipe de recherche, s'engage, le cas échéant, à protéger les renseignements personnels obtenus de la manière suivante :

A. En assurant la protection et la sécurité des données recueillies auprès des participants ou participantes et à conserver les enregistrements dans un lieu sécuritaire;
B. En ne discutant des renseignements confidentiels obtenus auprès des participants ou participantes qu'avec les membres de l'équipe;
C. En n'utilisant pas les données recueillies dans le cadre de ce projet à d'autres fins que celles prévues, à moins qu'elles ne soient approuvées par le CER de HEC Montréal. **<u>Notez que votre approbation à participer à ce projet de recherche équivaut à votre approbation pour l'utilisation de ces données pour des projets futurs qui pourraient être approuvés par le CER de HEC Montréal;</u>**
D. En n'utilisant pas, de quelque manière que ce soit, les données ou les renseignements qu'un participant ou une participante aura explicitement demandé d'exclure de l'ensemble des données recueillies.

Toutes les personnes pouvant avoir accès aux données ont signé un engagement de confidentialité.

Le CER de HEC Montréal a statué que la collecte des données liée à la présente étude satisfait aux normes éthiques en recherche auprès des êtres humains.

6. DÉROULEMENT DE L'EXPÉRIENCE

Cette section précise le déroulement de l'expérience.

- Avant le début de l'expérience, une explication du but de la recherche et du déroulement de l'expérience sera donnée au participant;
- Le participant devra ensuite signer l'accord de consentement qui présente les diverses conditions de l'expérience;

- Selon le cas, les outils de mesures des données oculométriques seront calibrés (2 à 10 minutes) aux endroits appropriés sur le participant et ce, avec son accord. On vous demandera de fixer des points précis sur l'écran de l'ordinateur.
- Par la suite, vous serez amené à utiliser différents outils informatiques pour réaliser des tâches.
- Selon le cas, nous vous demanderons de répondre à des questionnaires pour commenter votre perception de l'utilisation de ces équipements.

7. APRÈS L'EXPÉRIMENTATION :

- Selon le contexte de recherche, les participants seront invités à remplir un questionnaire post-expérimental.
- Un *debriefing* sera également offert aux participants en fonction du contexte de la recherche. Toutefois, aucune interprétation des données brutes ne pourront être fournies aux participants.

8. CONSENTEMENT DU PARTICIPANT

Êtes-vous âgé de MOINS de 18 ans?

OUI ¨ **NON** ¨

Avez-vous une correction de vue au laser ou de l'astigmatisme ?

OUI ¨ **NON** ¨

Avez-vous besoin de lunettes pour travailler à l'ordinateur ?

OUI ¨ **NON** ¨

Si vous avez répondu OUI à une de ces questions, vous ne pouvez **PAS** participer à cette expérimentation.

CONSENTEMENT A L'EXPÉRIMENTATION

Le chercheur, qui mène cette étude, m'a expliqué ce que je devrai faire durant l'étude et j'accepte d'y participer. Ni mon nom ou toute autre information permettant de m'identifier ne seront divulgués. Je comprends que toutes les informations que je fournirai seront gardées strictement confidentielles. De plus, je comprends que ma participation à cette étude est volontaire et que je suis libre de retirer mon consentement et de mettre fin à ma participation à tout moment.

¨ **J'accepte de participer à cette expérimentation**

¨ **Je refuse de participer à cette expérimentation**

9. SIGNATURES DU PARTICIPANT ET DU CHERCHEUR :

Prénom et nom du participant : ____

Signature du participant: ______________________________ Date (jj/mm/aaaa): _____________

Prénom et nom du chercheur : ____

Signature du chercheur : ______________________________ Date (jj/mm/aaaa): _____________

APPENDIX 5

INSTRUCTIONS INCLUDED WITH A ANONYMOUS QUESTIONNAIRE

EVALUABILITY AND TYPE OF SEARCH ON WEB

The following pages contain an anonymous questionnaire, which we invite you to complete. This questionnaire was developed as part of a research project at HEC Montréal.

Since your first impressions best reflect your true opinions, we would ask that you please answer the questions included in this questionnaire without any hesitation. There is no time limit for completing the questionnaire, although we have estimated that it should take about 5 minutes.

The information collected will remain strictly confidential. It will be used solely for the advancement of knowledge and the dissemination of the overall results in academic or professional forums.

The online data collection provider agrees to refrain from disclosing any personal information (or any other information concerning participants in this study) to any other users or to any third party, unless the respondent expressly agrees to such disclosure or unless such disclosure is required by law.

You are free to refuse to participate in this project and you may decide to stop answering the questions at any time. By completing this questionnaire, you will be considered as having given your consent to participate in our research project and to the potential use of data collected from this questionnaire in future research.

If you have any questions about this research, please contact the researchers involved in this project Gilmar D'Agostini Casalinho, and Dr Pierre-Majorique Léger.

HEC Montréal's Research Ethics Board has determined that the data collection related to this study meets the ethics standards for research involving humans. If you have any questions related to ethics, please contact the REB secretariat at (514) 340-6051 or by email at cer@hec.ca.

Thank you for your valuable cooperation!

Gilmar D'Agostini Casalinho
Ph.D. student
HEC Montréal
514-815-2241
gilmar.dagostini-oliveira-casalinho@hec.ca

Pierre-Majorique Léger
Professor
HEC Montréal
514-340-7817
pml@hec.ca

APPENDIX 6

Formulaire F
ENGAGEMENT DE CONFIDENTIALITÉ

Titre*: Evaluability and Type of Search on Web*

Identification du membre ou des membres de l'équipe de recherche :

Chercheur principal : Pierre-Majorique Léger
Chercheur : Gilmar D'Agostini Oliveira Casalinho
Chercheur : Sylvain Sénécal

Conditions de l'engagement :

Nous, soussignés, qui réalisons la collecte de données dans le cadre du projet de recherche mentionné ci-dessus, nous engageons formellement :

A. À assurer la protection et la sécurité des données que nous recueillerons auprès des répondants;

B. À ne discuter des renseignements confidentiels obtenus auprès des répondants qu'avec les membres de l'équipe de recherche;

C. À ne pas utiliser les données recueillies dans le cadre de ce projet à d'autres fins que celles prévues par le Comité d'éthique de recherche de HEC Montréal, soit la réalisation du projet de mémoire ou de thèse de Gilmar D'Agostini Oliveira Casalinho

D. À prendre les dispositions nécessaires pour protéger l'identité des répondants et en empêcher l'identification accidentelle tout le long de la collecte de données.

Prénom et nom du chercheur	Signature	Date (jj / mm / aaaa)
Pierre-Majorique Léger		
Gilmar D'Agostini Oliveira Casalinho		
Sylvain Sénécal		

APPENDIX 7

Participation à une expérimentation

Nous vous invitons à participer à une étude portant sur la comparaison de produits en contexte de commerce électronique. Vous allez être amenés à interagir avec un logiciel. Finalement, les participants répondront à un questionnaire après l'expérience. L'expérience devrait durer environ 60min et chaque participant se verra remettre un coupon d'une valeur de 20$.

Des mesures oculométriques seront utilisées lors de cette expérience afin mesure votre expérience usager.

- Nous allons collecter des données oculométriques pour calculer la direction du regard du sujet à l'écran. L'utilisation de l'oculomètre est complètement non intrusive. La lumière infrarouge utilisée ne comporte aucun risque.

Condition de participation

- Être âgé d'au moins 18 ans;
- Pouvoir travailler à l'ordinateur sans lunette de correction pour la vue ;
- Ne pas de avoir de correction de la vue au laser ;
- Ne pas avoir d'astigmatisme.

Pour participer

Si vous êtes intéressé par ce projet, veuillez vous inscrire sur le Panel de HEC Montréal (panel.hec.ca). Ce projet est réalisé par Dr. Pierre-Majorique Léger (Professeur, HEC Montréal) que vous pouvez joindre par téléphone au 514 340-7013, ou par courriel à l'adresse suivante : pml@hec.ca

APPENDIX 8

Projet: Evaluability and Type of Search on Web

Formulaire J

FORMULAIRE DE COMPENSATION POUR LA PARTICIPATION À LA RECHERCHE

Chaque personne qui participe à cette recherche recevra une compensation de 20$. Une telle somme vous sera versée en compensation du temps que vous consacrez à cette recherche. Il ne s'agit de pas d'une rémunération. Afin que nous puissions acheminer la compensation, les participants sont tenus de remplir ce document d'identification. Dans le but de maintenir l'anonymat des répondants, les documents d'identification ne pourront être rattachés aux questionnaires remplis une fois ces derniers retournés au chercheur.

Je confirme avoir reçu ma compensation de 20$ sous la forme d'une carte cadeau de la Coop HEC.

Nom du répondant	
Courriel	
Numéros des deux certificats	
Adresse :	
Ville :	
Code postal :	
N^o de téléphone :	
Signature	

Je suis intéressé(e) à participer à des expériences futures du Tech3Lab. J'accepte d'être contacté par courriel. Oui [ ] Non [ ]