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Investigating the Effect of Product Sorting and Users' Goal on Cognitive load

Seyedmohammadmahdi Mirhoseini
HEC Montreal, seyedmohammadmahdi.mirhoseini@hec.ca

Pierre-Majorique Leger
HEC Montreal, pierre-majorique.leger@hec.ca

Sylvain Senecal, Ph.D.
HEC Montreal, sylvain.senecal@hec.ca

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Pierre-Majorique Léger
HEC Montreal
pierre-majorique.leger@hec.ca

Sylvain Sénécal
HEC Montreal
sylvain.senecal@hec.ca

ABSTRACT

One of the most important goals of information systems is to minimize users' mental effort during decision making. Product sorting is a common way of displaying information for online consumers, which is designed to help them in order to find their desired products more efficiently. Product sorting may help users to make their product decision more conveniently depending on the criteria they have for choosing their product. Our goal in this study was to investigate how different product sorting (i.e., alphabetical, price) may decrease users' cognitive load during product evaluation phase depending on users' goal (i.e., product name, price). We expect that a match between goal and sorting type will decrease the amount of mental workload necessary for making a product decision compared to a mismatch condition. A two-factor (Product sorting X Users' goal) within-subject experiment was designed to test the hypotheses. Contributions to research and implications for practice are discussed.

Keywords

Cognitive Load, Product Sorting, NeuroIS, EEG

INTRODUCTION

Information display is an important element in online shopping, because on one hand it can be flexible and be designed in very different ways (West et al., 1999) and on the other hand it affects consumers' decisions and behaviors (Cai & Xu, 2008). Product result pages often provide different types of item sorting (e.g., alphabetical, price), which is an instance of changing information display. Sorting may act as a decision support tool for consumers (Sharkey et al., 2009). It changes information display in order to help consumers find their desired products (Ariely, 2000). Similar to other decision support tools, sorting can be used to improve users' decision making. However, it is not clear under what conditions various types of sorting may decrease or increase users' cognitive effort during the decision making process.

Minimizing cognitive load is important for users in shopping, and it is even more important when it comes to shopping for low value products. There are two ways that sorting may contribute to the enhancement of decision making: 1- Improving decision quality and 2- Saving users' cognitive effort (Todd & Benbasat, 1992). Researchers have found that the trade-off between the two factors (maximizing accuracy and minimizing effort) depends on the task and the context (Payne et al., 1988, Beach & Mitchell, 1978). For instance, it is more likely that consumers put effort to get more accuracy in buying an apartment than a cell phone. We use the same logic to explain how sorting may affect users' level of mental effort in shopping for low price goods. In shopping for these goods, consumers are expected to neglect decision accuracy in favor of minimizing mental effort. It is also important to understand how sorting affects users' cognitive load because it is a predictor of user satisfaction in online shopping (lo Storto, 2013). It means that product sorting could increase user satisfaction with the shopping process; however, these conditions need to be explained theoretically and be tested empirically.

Previous research suggests that a proper information sequence can result in an easier decision making process (Schkade & Kleinmuntz, 1994). This effect is contingent upon the alignment of information sequence with what users are looking for. Information sequence can facilitate the decision process if it increases the accessibility of right information for users. In this study, we design a two factor experiment (Product sorting X Users goal) and hypothesize that if product sorting matches users' goal, it decreases user cognitive load. To test our hypothesis we need to address the challenge of cognitive load measurement. Cognitive load is hard to capture using self-perceived measures because there are processes in the working memory that are beyond the consciousness of our brain. Thus, we use electroencephalography (EEG) to measure cognitive load during user-IT interaction.

Our study contributes to research by showing that how the sequence of information (i.e., sorting) affects users' cognitive load in their decision making process. We model this effect as a link between a fit construct (i.e., match between product sorting and user goal) and cognitive load. It also has implications for practice by showing how different types of product sorting that are being used in shopping websites can reduce users' mental workload, which in turn may increase consumers' satisfaction with their shopping experience.

LITERATURE REVIEW

Researchers propose that users seek to maximize their decision quality and minimize the cognitive effort exerted during this process (Todd & Benbasat, 1992). Consumers, depending on the context, find a trade-off between the two factors, and make their product decision. However, in some contexts, the relative importance of decision quality is negligible compared to that of minimizing cognitive effort (Bettman et al., 1998). For instance, compare shopping for an apartment and grocery items. Any mistake in the former decision may have serious effect on users' life and be hard to recover, whereas in the later they are less sensitive to the accuracy of decision because in the worst case it will be easy to buy another product. Even generally, cognitive effort is proposed to be more weighted than accuracy (Todd & Benbasat, 1992). The reason behind this phenomenon is that the feedback from effort expenditure is immediate compared to feedback from accuracy, which takes more time to operate (Kleinmuntz & Schkade, 1993). Therefore, accuracy is sacrificed in favor of saving cognitive load, and the intensity of such sacrifice depends on the decision making task and context.

Cognitive effort is an important factor in explaining human decision making. It is considered as the cost of decision making for users (Todd & Benbasat, 1992). Cognitive load is defined as the set of mental resources used by people to encode, activate, store, and manipulate information while they perform a task (DeStefano & LeFevre, 2007). A key to understanding cognitive load and its effect on human behavior is that these mental resources are limited (Wickens, 2002). Therefore, efficient use of working memory is a key factor to prevent users from overload situations and provide them with a satisfying shopping experience (lo Storto, 2013). In an online shopping session, any website element that fails to provide users with the critical information needed for making product decisions reduces cognitive efficiency of the website (lo Storto, 2013). This failure could be either not providing necessary information or presenting redundant information for users. Poor design of shopping websites means that consumers need to devote more working memory resources (e.g., attentional capacity of working memory) in order to accomplish the shopping task. There are a number of factors that affect users' cognitive workload, among them are different ways of information presentation, which includes form (numerical, pictorial, verbal), organization (table, matrix, list, paragraph, hierarchical cluster), and sequence (random, ascending or descending on an attribute value, alphabetical, chronological) (Kleinmuntz & Schkade, 1993, Todd & Benbasat, 1992).

In the online shopping environment, product sorting is a form of information sequence modification. It creates a new information presentation for consumers to help them in making product decision. Sorting arranges products based on a specific attribute and helps consumers to narrow down their consideration set (Sharkey et al., 2009). In this sense, sorting can be considered as a simple decision support tool because one of the functions of decision support systems are screening and sorting alternatives (Van der Heijden, 2006). It supports consumer decision making by determining the relative utility of alternatives (Häubl & Trifts, 2000). Therefore, it contributes to the minimization of consumers' mental workload. Consumers will be able to screen alternatives and reduce the universal set to consideration set more easily.

Online shopping tasks can be classified into two general groups based on consumers' goals: searching versus browsing task (Carmel et al., 1992). In searching tasks, consumers' objective and criteria is clear (Hong et al., 2004). They know in advance what product they are looking for. For instance, they know the brand name of the product. In contrast, consumers who are engaged in a browsing task have no specific criteria (Hong et al., 2004). For instance, they only have the intention to buy a TV, however, this does not mean that they do not have any criteria while purchasing the TV. In the current study, we are focusing on search tasks, in which consumers have a specific criteria for shopping.

HYPOTHESES DEVELOPMENT

Our study suggests that product sorting affect users' mental workload depending on the goal of users. Product sorting (i.e., listing products based on the sequence of their values) can decrease users' cognitive effort; however, this effect is depends on its alignment with users' goal . Figure 1 illustrates our research model.

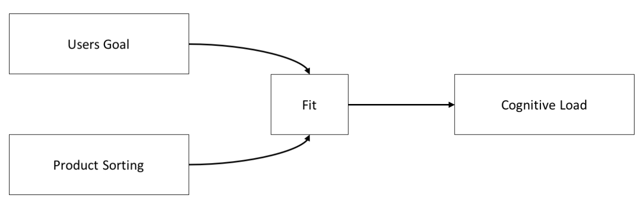

Figure 1-Research Model

We model the contingent effect of product sorting and users' goal as a fit construct. Venkatraman (1989) proposed six conceptualizations of fit constructs including fit as matching. Matching represents the fit between two constructs without reference to a criterion construct, however its effect on different set of criterion variables can be investigated. Therefore, we have either "match" or "mismatch" conditions between users' goal and product sorting. In match conditions, product sorting assists users to find the target product whereas in mismatch conditions, there is no complementarity between the two variables and users experience more mental workload to find the target product compared to a match condition. Table 1 shows match and mismatch conditions.

		Goal	
		Price	Name
Sorting	Price	1	2
	Brand	3	4
		Match	Mismatch

Table 1- Match Table

As stated, product sorting as a decision support tool helps consumers to make their product decision more efficiently (Cai & Xu, 2008). Consumers will be able to remove a number of items from universal set without devoting attentional capacity of their working memory. We argue that if users' goal matches product sorting on a website, it reduces users' mental workload. For instance, users who are looking for the cheapest product, will be supported by sorting products based on price. Sorting based on brand name will not be useful for them because they need to screen all the product prices. Thus, our hypothesis is: *H1: Users experience less mental workload when users' goal matches product sorting compared to mismatch conditions.*

METHODOLOGY

Experimental Design

A 2 (Product sorting) X 2 (Users' goal) within-subject experiment was designed to test the research hypothesis. Two types of product sorting (Price and Alphabetical) are manipulated in a search result page with ten products (in two rows) as shown in Figure 2.

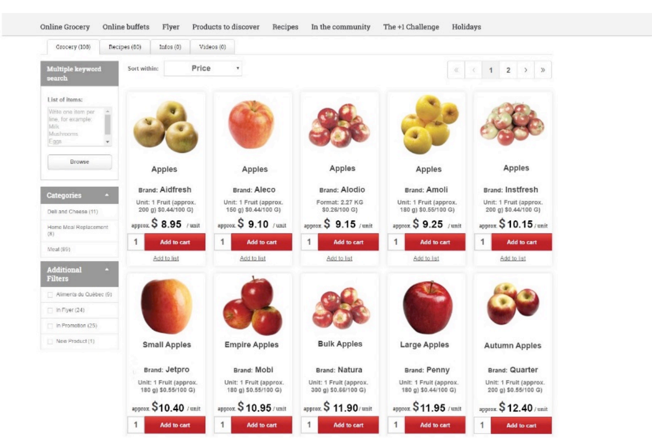

Figure 2- A sample result page

Ten experimental tasks were designed for each condition with different products, which means each participant performed 40 tasks in total. There was no time limit for performing each task, and after selecting the product, they were automatically presented with the next task. In each condition half of the products were perishable (e.g., fruits, vegetables, meat) and half non-perishable (e.g., flour, cereal). The product results pages are screenshots that are designed based on a popular regional online grocery website. Participants were asked to select a product based on either price or a specific brand name, and the products are sorted based on either price or alphabetically. The experiment was designed using E-prime software. The brand names were fictitious and unknown to participants. We used product pictures from a real online grocery website. Any brand name or logo were removed from the pictures.

Sample and Procedure

Twenty one subjects (N=21; 48% female) were recruited from a university panel to participate in the experiment. They were compensated with a 30$ gift card. Participants were first greeted and then asked to read and sign the consent forms. Then, EEG headsets were placed on participants and impedance was tested to ensure of the quality of EEG data. Then, the experiment started and participants went through the experimental protocol according to Figure 3. They first filled out the questionnaire, then read the experiment introduction message. A sample page was shown to participants to familiarize them with the experimental task. In the next three pages, the sort box, price tag, and brand names were highlighted respectively to make sure participants know where to find them on the page. Then, participants were asked to perform a sample test and ask any question about the experiment. Lastly, they started performing the tasks, which were randomized. This study was approved by the ethical committee of our institution.

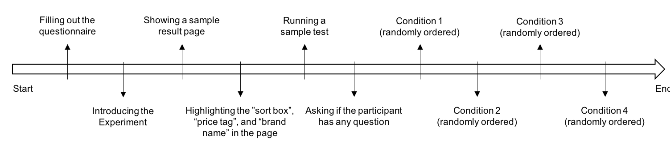

Figure 3- Experiment Procedure

Measurement

We used EEG to measure cognitive load. More precisely, we used the Event-related Potential (ERP) method, which was developed based on EEG (Léger et al., 2014). EEG measures the activity of a large group of neurons firing at the same time, and therefore, it is difficult to separate a specific cognitive process associated with that neural activity (Riedl et al., 2010). The ERP method overcomes this problem by presenting stimuli several times and measuring users' response to them. This would cancel the neural activities unrelated to experimental manipulation (Léger et al., 2014). Thus, it is crucial to have the exact timing of stimulus presentation to measure the neural activities associated with it. We used participants' responses time to create these events. The exact time that participants click on the target product is when they have made their decision. ERPs were calculated based on these time stamps.

ERPs consist of a number of important components. These components are found to be sensitive to different cognitive, emotional, and behavioral variables (Riedl & Léger, 2016). An ERP sample is illustrated in Figure 4. Components' names represent both the polarity and approximate latency of the element. For instance, N100 is a negative peak, which occurs approximately 100 ms after the stimulus presentation.

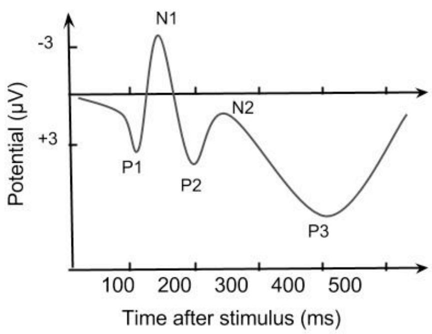

Figure 4- Event Related Potential Components

In this experiment we use the P300 component to measure users' mental workload. This component is a positive peak, which can be observed approximately 300 ms after the event presentation. It has been found that the amplitude and latency of P300 are sensitive to users cognitive load (Murata et al., 2005, Uetake & Murata, 2000). Research shows that P300 amplitude is negatively linked to the users' level of cognitive processing load (Ullsperger et al., 1988). P300 latency is also increased with the task difficulty (Ullsperger et al., 1986). Therefore, in this study we use P300 amplitude and latency to measure users' cognitive load associated with making product decisions. Experience with online shopping and grocery shopping were also measured at the beginning of the experiment to control for the effect of various types of experience on users' cognitive effort.

Data Analysis (Ongoing)

To process the EEG data, we use Brainvision Analyzer and MATLAB software. EEG raw data was filtered using a FIR filter of order 96 between 0.1 and 30 Hz as explained in the Zeyl et al., (2016). Then the EEG was re-referenced to the average of all electrodes. Independent component analysis (ICA) was performed to identify the bad components such as eye-blinks and muscle movements. The components were removed and then, the signal was reconstructed in the time domain using inverse ICA. The signal was then segmented with respect to the mouse clicks time stamps between -200 and 800 ms of the events. As of now, we have generated these segments and are performing the remaining data analysis steps. There are 10 segments per condition (10 tasks) and 40 per subject (10 tasks X 4 conditions). The segments have to be averaged for each condition to create a single ERP per condition. To better identify P300 peaks and latency, another filter between 0.1 and 20 Hz will be applied to the averaged segments. Using peak detection feature in Brainvision, the P300 components will be identified and the amplitude and latency of the peak will be extracted. These two measures will be used to test the research hypotheses.

Conclusion

In this study we investigate the contingent effect of product sorting and users' goal on their level of cognitive load. We argue that product sorting will decrease users' cognitive load for making product decision if it matches users' goal. Our study will contribute to theory by uncovering the effect of information sequence on users' cognitive load. It will also contribute to methodology by introducing a new way of measuring cognitive load during online shopping tasks. ERPs can be used in other user-IT transactions to measure users' cognitive load. This research will also have implications for practice by showing how product sorting can reduce users' cognitive load. This is important since cognitive load is a predictor of user satisfaction in online shopping context (lo Storto, 2013). This study suggest avenues for future research as well. In this research, we study how users with pre-defined goals (i.e., finding the cheapest product or finding a specific brand) are affected by websites product sorting features. However, the constructive view of consumer decision making suggests that many users do not have a clear predefined set of preferences to make product decisions (Payne, Bettman, Coupey, & Johnson, 1992). Their preferences and criteria for making product decision are constructed in response to a number of tasks, contextual, and individual difference factors. Prior knowledge or expertise can affect the construction of individual preferences (Payne et al., 1992). Therefore, users who have no predefined strategy for decision making, may construct a set of preferences based on a number of factors. Studying these conditions are of interest to both research and practice.

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