Information Overload in Processing Consumer Reviews: The Role of Argumentation Changes

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Abstract. Information overload theory suggests that consumers can only process a certain amount and complexity of information. In this study, we analyze whether information overload can also occur while processing individual product reviews with a high rate of argumentation changes. An argumentation change denotes a change from positive to negative arguments, and vice versa. We propose a NeuroIS experiment in which participants are presented a given set of product reviews with a low or high rate of argumentation changes. The participants are asked about their perceived helpfulness of the product review, their purchase intention for the product, and self-reported information overload. During the experiment, we measure cognitive activity based on electroencephalogram (EEG) and eye-tracking. We expect that a higher rate of argumentation changes is linked to greater cognitive activity, and, in particular, lower perceived review helpfulness and purchase intention.

Keywords: Product reviews, Purchase Decision-Making, Information Overload, E-commerce, NeuroIS

1 Introduction

Modern retailer platforms provide customers with the opportunity to view product reviews from other customers as part of their purchase decision-making process [1, 2]. Research has demonstrated that potential customers are more receptive to reviews that are perceived as more helpful [3], and that these reviews consequently have a stronger influence on sales numbers [4]. As such, product reviews serve as focal point for the study of human purchase decision-making [1, 5–8].

Customers are generally provided with a large number of product reviews. Prior studies have shown that a high number of product reviews is likely be overwhelming, and, thereby, cause information overload [9–11]. The concept of information overload suggests that customers can process a limited amount and complexity of information. Once this limit is reached, additional information is no longer useful for customers for their purchase decision-making [12, 13]. While information overload is well studied on the product level with respect to the number of product reviews, little is known about how individual reviews can cause information overload.

In this study, we propose a NeuroIS experiment to analyze whether information overload can be caused by product reviews with a high rate of argumentation changes. Product reviews can be written in several ways. A review can be one-sided, so that it either mentions positive or negative aspects only, or two-sided with a mixture of positive and negative arguments. Two-sided reviews can then be structured in multiple ways with different rates of argumentation changes. The review can start with positive arguments followed by negative arguments and vice versa. Both structures exhibit only a single argumentation change. Alternatively, the review can alternate between positive and negative arguments, which implies a higher rate of argumentation changes. It may thus become difficult for customers to comprehend the review and the review may consequently be perceived as helpful and encourage the purchase decision. During the experiment, we measure cognitive activity using EEG and eye-tracking as an indication of information overload.

2 Research Hypotheses

2.1 Information Overload

The term "*information overload*" was coined by Gross [14]. The concept of information overload suggests an inverted U-shape relation between information load and decision outcomes, such that consumers make the best choices when being provided with a medium amount of information, and the worst choices when being provided with little or too much information [12, 15, 16]. On most retailer platforms, product reviews are provided in the form of a star rating and a textual description [17, 18]. The textual descriptions details prior experiences and pros and cons of a product [19]. Reviews can be one-sided, i.e., arguing strictly in favor of or against a product, or two-sided, i.e., enumerating pros and cons at the same time. Existing research found that two-sided reviews are perceived as more credible [20, 21] and more helpful [22, 23]. A two-sided review can be written in several ways, by enumerating pros followed by cons, cons followed by pros, or by interweaving pros and cons [24]. We argue that a higher rate of argumentation changes increases information complexity [25], which increases the required cognitive load to comprehend the review. We therefore propose

Hypothesis 1a (H1a). *A higher rate of argumentation changes in a product review is linked to increased cognitive activity.*

Hypothesis 1b (H1b). *A higher rate of argumentation changes in a product review is linked to higher self-reported information overload.*

2.2 Helpfulness and Purchase intention

Information overload theory suggests an inverted U-shape relation between information load and decision outcomes. Accordingly, consumers are expected to make the worst choices when being provided with little or too much information [12, 26]. Interestingly, information overload can also occur when information complexity is high [27, 28], since a higher amount of cognitive load is required. Assuming that a higher rate of argumentation changes in a review is linked to information overload, we argue that a review with a high rate of argumentation changes is harder to comprehend and thus less helpful. Furthermore, previous work has linked information overload to a reduced consumer experience [29]. For instance, [30] found that information overload could have a damaging effect on the way users view the merchant and on their commitment to learn about the product's specifications. Another study found the utilization of the information within reviews to be dependent on the processability (simplicity/complexity) of the text [31]. Hence, we argue that a higher rate of argumentation changes in reviews has a negative impact on purchase intention.

Hypothesis 2a (H2a). *A higher rate of argumentation changes in a product review is linked to a lower perceived helpfulness.*

Hypothesis 2a (H2b). *A higher rate of argumentation changes in a product review is linked to a lower purchase intention.*

2.3 Low- and High-Involvement Products

Products can be classified into low- and high-involvement products. Due to a lower price and less durability, low-involvement products feature a lower perceived risk of poor purchase decisions [32, 33]. High-involvement products, on the other hand, feature a higher price and greater durability, and therefore a higher perceived risk [5, 32]. Due to their higher perceived risk of making poor purchase decisions for high-involvement products, consumers have an incentive to invest more cognitive effort into collecting product information (including product reviews) for high-involvement products than for low-involvement products. Thus, one could argue that the effect of argumentation changes on information overload, review helpfulness, and purchase intention is stronger for high- than for low-involvement products. Conversely, one could argue that customers seeking information for high-involvement products are already geared towards investing greater cognitive efforts. A greater information complexity in comparison to other reviews may then a smaller effect. To keep track of both concepts, we propose

Hypothesis 3 (H3a). *The effect of the rate of argumentation changes on review helpfulness and purchase intention is stronger for high-involvement products than for low-involvement products.*

Hypothesis 3 (H3b). *The effect of the rate of argumentation changes on review helpfulness and purchase intention is stronger for low-involvement products than for high-involvement products.*

3 Method

3.1 Materials

We manually generate product reviews based on an existing dataset of product reviews from Amazon [34] as this is the prevalent choice in the related literature when studying product reviews (e.g., [5, 35–37]). We select online reviews for one particular low- and one high-involvement product. The low-involvement product is given by a package of Starbucks ground coffee and the high-involvement product is given by a digital camera [38]. We also retrieve the descriptions of both products as shown on Amazon. We then generate eight reviews with a low and high rate of argumentation changes for each product type, which yields a total of 16 reviews per product. First we selected original reviews from the existing review dataset.Then we manually changed these reviews, to disconnect sentences (e.g. removed words such as "Therefore", "And this is why", etc.). Thereby, we increased individual sentence flexibility of being positioned elsewhere within the review (see section "Treatment"). We remove the specific product name from the product description and from the presented reviews. This accounts for potential biases against a given brand among the participants.

3.2 Treatment

We modify the rate of argumentation changes as high (treatment) and low (control) by manually editing the product reviews. The participants are then randomly assigned to the treatment or control group. Each participant of the control group is presented a total of 32 control reviews, while each participant of the other group the same amount of treatment reviews. The order of reviews is randomized.

3.3 Procedure

The experimental procedure can be described as follows. First, we calibrate the EEG and eye-tracking devices. Subsequently, we perform a test run with a different review to make the participants familiar with the general procedure. The product review is displayed, without any images or product description. For each review, participants are given an arbitrary amount of time for reading. We decide against a fixed time limit as we do not intend to induce any kind of time pressure. We then ask the participant three items on 7-point Likert scales, namely, perceived review helpfulness from 1=not helpful to 7=very helpful, the purchase intention from 1=don't buy to 7=strong buy, and self-reported information overload from 1=none to 7=strong. After all reviews are shown, participants fill out a survey, where they provide their age, gender, propensity to trust, experience with online purchases, and experience with the two products (ground coffee and digital camera).

3.4 Participants

We determine the required sample size for the experiment using "GPower". Assuming an effect size of d = 0.10 (due to neurophysiological measurements), alpha = 0.05, and power = 0.80, and a dataset of 32 reviews, the analysis suggests a sample of at least 50 participants (1,600 observations). The subjects are recruited via student mailing lists and announcements during lectures. Ethics approval was granted by the University of Freiburg. Each participant receives a fixed compensation of 12 Euro.

3.5 Measures

We measure cognitive activity/load as a proxy for information overload by using EEG and eye-tracking. Besides, we ask the participants for self-reported information overload as a manipulation check. EEG is a non-invasive brain imaging tool, which records the electrical activity in the central nervous system. These electrical signals form wave patterns at specific frequencies. Hence, EEG measures the magnitude and detects detects the location of brain activity involved in a certain task [39]. The importance of alpha waves (8-13Hz) and their link to certain mental processes has been shown by previous work [39, 40]. When a certain brain region becomes active, alpha waves desynchronize, which results in lower alpha levels [41]. Hence, the desynchronization of alpha waves is an indicator for higher levels of cognitive activity [42–44]. To perform our EEG study, we use a 14-channel Emotiv wireless EEG device, which has been used by a range of previous work [45, 46, 46–48].

To study the participant's changes in eye movements, we use the Tobii Pro Fusion screen-based eye-tracking device, which is a state-of-the-art device that captures data at speeds up to 250Hz. Several eye-tracking measures have been linked to changes in cognitive load. Zagermann et al. [49] suggest a correlation between cognitive load and several eye movements. Particularly eye fixations and saccades were found to be indicative of major changes in cognitive load. Furthermore, fixation duration has been shown to be positively correlated with increasing cognitive load [50]. Hence, we use eye fixations and saccades to operationalize cognitive load based on eye-tracking.

4 Expected Contributions

We expect to find support for our hypotheses H1a, H1b, H2a, H2b, and H3a. In particular, we expect to demonstrate that alternating between pros and cons about a product review can lead to situations of information overload. Concordant with information overload theory, we expect that a higher rate of argumentation changes is linked to lower review helpfulness and purchase intention of the given product. The findings from the experiment should have important implications for IS research and practice. To the best of our knowledge, this study is the first to analyze the line of argumentation in product reviews through the lens of NeuroIS. While existing studies on information overload often rely on self-reported data only, which may not be as accurate as external measurements [51], this study employs EEG and eye-tracking devices to measure the effects of argumentation changes. In line with the inverted U-shape theorem around information overload theory, we expect to identify the "right" amount of argumentation changes, which does not lead to information overload. From a practical perspective, our findings allow retailers (particularly their review system designers) to gain a better understanding of human information search behavior. This could help them present more helpful reviews to their customers, which subsequently increase their purchase intentions.

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