Consumers' Need for Negative Product Information Before Reading Reviews

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Abstract

Negative product-related information is crucial to consumers in purchase decisions. Consumers perceive negative information stronger than positive, and next to a stronger perception, consumers also have a high demand for negative product aspects, as these show the problem areas of a product and can help avoid losses. But negative product-related information is not available in the product search process until the customer reads reviews at a very late phase of the decision process. Even though we know about a bias in perception of negative information, little is known about the exact need for negative product-related information during the search process. We examine the need for negative product-related information throughout the purchase-decision process for different product types. Insights about the need for negative product-related information can inform ecommerce platform providers how to design a better product search on their site.

1. Introduction

Negative product-related information[1] plays a critical role in consumer's purchase decisions [1]. According to information processing theory, consumers perceive negative information even stronger than positive information [2,3], emphasizing the importance of negative information. Further, consumers appreciate negative reviews because negative reviews show the issues of a product, e.g., when the battery of a device tends to overheat, and can help avoid losses [4]. From positive reviews, in contrast, consumers are less able to find out the critical aspects of a product.

The main source of negative product-related information is user-generated content[2] in online reviews, which we call product-related user-generated content (PUGC) in the following. This information source is also very rich, as it reflects a multitude of experiences, each with a different focus. Besides the importance of negative PUGC and the richness of online reviews as an information source, it is questionable if ecommerce platform providers use negative PUGC in the optimal way. Negative information is rarely searchable in the product search. As an example, when searching for a laptop, it is possible to search for a large hard disk, but not to search for all laptops without a noisy fan. Interestingly, the information that really seems to matter to consumers (which is reflected and manifested in what they write about in their reviews), is not available during filtering. Reviews are only accessible after a product has been found [5], and are treated like an extension to the vendor's product description. Searchability (in terms of keywords or filters) of negative PUGC can therefore be an important feature that is so far not implemented in common ecommerce platforms. Indeed, mechanisms exists to present negative reviews more prominently or on equal footing with positive reviews, but the user still has to read all the negative reviews and click on every single product first, before being able to access the negative reviews. Although some users read negative reviews first, the evaluation of products is still a time-consuming task, as users have to iteratively refine their image of the product, confirm hypotheses about product features with other reviews etc. It would be much more efficient for users to exclude all products with, e.g., mentions of a noisy fan from their result set up front. We exemplify the situation in a simplified scenario: Without searchable negative PUGC, the user has to 1.) filter /search for products with a large hard disk first, and 2.) eliminate all products with a noisy fan in a

[1] As information in a literal sense is neither positive nor negative, we define negative product-related information as information that describes aspects of a product which are negative in the view of a consumer.

[2] The creation of product-related content by users is often referred to as electronic word of mouth (eWOM). Whereas the term eWOM is sometimes used in the literature to describe content, in this study, eWOM is understood as a process, not the textual product of the process, which is denoted with PUGC.

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manual, time-consuming process of reading all reviews. In contrast, with searchable PUGC, the user can obtain a result set with higher accuracy referring to his/her needs much quicker by *directly* excluding products with reviews mentioning a noisy fan.

Consumer reviews offer a form of peer learning among consumers by enabling other consumers to learn from past experiences [6]. In shopping contexts, there is often a need for negative product-related information, and probably already *before* reading reviews. As the number of online reviews increases, the need to organize and rearrange product-related information, both positive and negative, becomes more important [7]. Providing negative product-related information in earlier phases of the purchase process means getting away from the pure display of great text amounts, but providing the information in an aggregated and consolidated way, i.e., to transform many former experience attributes of a product into search attributes [8,9]. Of course, it is challenging for information systems designers to pull product-related information from reviews "in front of the product", not just from the technical perspective, but also from the perspective of information needs. But it is a straightforward thought to make PUGC, which has characteristics of "search attributes", also available for search and filter activities. For such a design, little is known about how user interfaces should look like, and how many negative product-related information consumers prefer in contrast to positive product-related information.

Studies on negativity bias have already shown that negative information is perceived stronger than positive information [1,4,10], and that the extent of this biased perception depends on the product type [3]; it has however not been examined whether the consumers' need for negative information is stronger than the need for positive information and if it also differs with the product type (as the consumer's perception of negative information does [11]). Combining the question of the need for negative product-related information with the question of an early availability of negative information in the search process, we formulate the following research question:

How does the need for negative product-related information change throughout the purchase process (in comparison to the need for positive product-related information)? And does the product type influence the need for negative product-related information?

The remainder of this paper is organized as follows. In Section 2, theoretical background and related work from three fields is introduced, namely, negativity bias in consumer purchase behavior, purchase-process models, and approaches to integrate review information into early purchase-process phases. In Section 3, the research approach and conceptual model to investigate the need for negative information throughout the purchase process depending on product type are depicted. Further, the survey instrument and data analysis propositions are explained. Results are presented in Section 4 and discussed in Section 5. We conclude with our contribution to negativity bias theory, that not only users' perception, but also users' need for negative information varies with the product type, and our contribution to practice, how ecommerce platform providers can use that knowledge to better design their web shop experience.

2. Related work and theoretical background

First, we relate to existing literature in the field of the negativity bias in consumer purchase behavior and purchase-decision processes as we combine both concepts in our research. Further, we give some notes about corresponding approaches and methods to extract relevant product features (positive and negative) from reviews as a basis for its use in early phases of the purchase process.

2.1 Negativity bias in purchase behavior

The negativity bias denotes the effect, that things of a negative nature have a greater effect on a person's psychological state than do positive or neutral things [12]. The notion of the negativity bias reaches back to psychology research, e.g. [10,13]. Since then, the negativity bias has been investigated within many different domains, such as attention [14], decision-making and judgement [15], evaluations [16], and learning. A profound analysis of the negativity bias was performed by Rozin and Royzman [17].

With the emergence of user-generated content and electronic word-of-mouth (eWOM), the negativity bias has been widely adopted by studies in the information systems domain. Several studies investigate the negativity bias with respect to consumer purchase behavior and the helpfulness of online reviews. For example, Yin et al. [4] found that negative reviews are more specific, have higher surprise value, and increase the ability to avoid losses. Sen and Lerman [3] found that readers exhibit a negativity bias for utilitarian product reviews only. Also differentiating on the product type, Pan and Zhang [11] found that both review valence and length have positive effects on review helpfulness, and the product type (i.e., experiential vs. utilitarian product) moderates these effects. Also, Park and Lee [2] find that the eWOM effect is greater for negative eWOM than for positive eWOM. Lee et al. [18] examine the proportion and quality of negative online consumer reviews from the perspective of information processing using the elaboration likelihood model. Xue and Zhou [19] investigate on the impact of negative and positive eWOM information in relation to message credibility, brand interest, purchase intention, and forwarding intention. Wu [20] has shown in empirical studies that the negativity bias can be attenuated or even reversed in the context of eWOM.

2.2. Purchase-decision process models

Information processing theory identified three decision-making phases [21,22] in pre-internet times—intelligence, design, and choice—which have since been adapted to online purchase decision making [23]. In general, when talking about the purchase-decision process, the consumer purchase funnel model [24] is widely used in various forms and under differing names (e.g., the consumer decision journey [25]) or in diverse “funnel models,” such as the ecommerce funnel, sales funnel, or conversion funnel. The consumer decision model [26,27] proposes seven phases as one of the most detailed models: need recognition, search for information, pre-purchase alternative evaluation, purchase, consumption, post-purchase alternative evaluation, and divestment. Several other theories have been applied to the decision-making process, such as mental accounting theory [28]. Vázquez et al. [29] presented a novel analysis and classification of product-related information in terms of how it is involved in the phases of the consumer decision journey. Mudambi et al. [30] use a six-phase purchase process that even goes beyond the purchase (need recognition, information search, evaluation of alternatives, purchase decision, purchase, and post-purchase evaluation). Depending on the perspective, purchase-decision models have a different number of phases (three to seven) with different names. Throughout this study, “purchase process” and “purchase funnel” are used to identify the funnel model and the underlying purchase process.

2.3. Integrating negative product-related information into early purchase process phases

The technical perspective of how to aggregate and consolidate negative product-related information from reviews and how to integrate them into earlier phases of the purchase process are a necessary prerequisite for making negative PUGC available during product search and filtering. Several approaches and frameworks have been proposed to analyze and aggregate reviews, e.g., [31–34].

Two papers are worth mentioning in the context of this paper, as they line out applications to aggregate product features mined from UGC and integrate them into a product search process: First, Huang et al. [5] present RevMiner, an extractive user interface that allows users to search for restaurants (e.g., “Mexican food, good service”) and compare them. Second, Feuerbach et al. [35] propose an approach to integrate mined product features in form of search facets to build an interactive hotel search. However, both approaches did not take negative product features into account. Still to mention is, that although approaches have been proposed how to mine product features out of textual data and aggregate them, these approaches have rarely been applied in practice so far. One of the reasons might be that it is still unclear which information need for user-generated content exists in each phase of the purchase process.

3. Research approach

The research approach combines findings about the negativity bias as part of information processing theory with a purchase funnel model in order to obtain a dynamic view (over the phases of the purchase process) on the need for negative product-related information for different product types. The following depicts how both negativity bias and purchase funnel apply to the research objective.

3.1. Conceptual model

The conceptual model comprises three constructs – the need for negative product-related information, the consumer’s phase in the purchase funnel, and the product type (Figure 1). In the following, we will explain the three constructs.

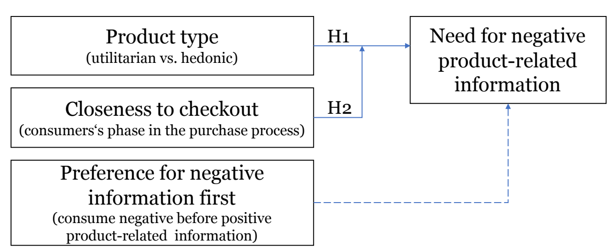

Figure 1. Conceptual model

3.1.1. Construct 1: Need for negative product-related information. The need for negative product-related information can be interpreted as a facet of user requirements. The construct denotes the need for negative PUGC in comparison to positive PUGC. For practice, the need for negative PUGC is a relevant construct as it may directly inform information systems designers which type of information (negative or positive) is needed by users when designing a system based on product reviews.

3.1.2. Construct 2: Closeness to checkout. In this research approach, a parsimonious model of a purchase funnel was used that consists of three phases (see Figure 2): (1) a screening phase, during which the user gathers an overview about products; (2) a filtering phase, during which the user narrows down the consideration set; and (3) an evaluation phase, during which the user reads product-related information (i.e., descriptions and reviews) in detail.

The following gives an overview of what positive and negative product-related information means in the three different purchase funnel phases.

PUGC in the screening phase. Screening PUGC is the first step in the purchase process. "In the beginning phases of purchase, a buyer lacks experience, his choice criteria is not well-developed and he doesn't have any knowledge of various brands and their potential" [28, p. 27]. PUGC must be extracted from reviews, aggregated, consolidated, and condensed to be presentable in the screening phase.

PUGC in the filtering phase. Filtering PUGC is the second step in our purchase process model. If users should be able to filter for PUGC, it must be aggregated, consolidated, and condensed just like in the screening phase. Furthermore, we obtain two types of filters, positive and negative (include positive PUGC resp. exclude negative PUGC). The difference between screening and filtering is not the presentation of the PUGC but the functionality a filter provides.

PUGC in the evaluation phase. Evaluating product-related information is the last step in the purchase process. In this phase, the user reads detailed information about every product in detail (i.e., the full text of the review). Figure 2 depicts examples of positive and negative PUGC in each of the three phases.

3.1.3. Construct 3: Product type. Different product type classifications can be found in the literature. In general, our research objective implies the focus on consumer goods. Consumer goods are often classified into convenience goods, shopping goods, specialty goods, and unsought goods [36]. It is also possible to distinguish material from immaterial goods. The theory of information economics distinguishes products according to information asymmetry, i.e. search good, experience good, and credence goods [37]. Another classification is the separation of utilitarian and hedonic products [3,38] or utilitarian and experiential products [11], whereas experiential goods also refer to hedonism.

While all these product differentiations might be worth examining, for our study, we chose to investigate on the differentiation of utilitarian and hedonic products, as this is the differentiation chosen by Sen and Lerman [3], which we base our hypotheses on, so we are better able to align our research to existing research. Utilitarian products are usually interesting to consumers because of their functionalities, and consumers' judgement is usually cognitively driven, instrumental and goal-oriented [39]. Hedonic products, in contrast, are characterized by aesthetic or sensual pleasure, fantasy, and fun [40]. Consumers judgement on hedonic products is more personal and emotional. Huang et al. found that consumers tend to seek and process product-related information differently between utilitarian and hedonic products [41].

3.2. Hypotheses

From studies on customer reviews, we know that a) the product type influences a user's review valence [3], showing a greater negativity bias effect for utilitarian products than for hedonic products, and we also know that b) consumers appreciate negative reviews, because negative reviews show the issues of a product and can help avoid losses [4]. Putting together both a) the negativity effect depending on product type and b) the need for negative information, we can formulate the hypothesis that the product type also influences the need for negative product-related information. Hence, we hypothesize:

H1: The *need for negative product-related information* varies with the *product type*. A utilitarian product induces a higher need for negative product-related information than a hedonic product.

Next to showing this primary effect of H1, we seek to investigate whether the consumer's phase in the checkout process has a moderating effect on the need for negative product-related information. We know that information needs may vary throughout the purchase process [42], and therefore aim at obtaining a dynamic view. In the different stages of the purchase process, users have to fulfill different tasks. With different tasks, also information needs may vary, and the need for information may be assessed differently. We therefore formulate H2 as follows:

H2: The *consumer's phase in the purchase process* has a moderating effect on the effect of product type on the need for negative product-related information.

Some consumers might have a *general* preference (irrespective of purchase phase or product type) to read negative reviews prior to positive reviews. To control for this potential influence and isolate it from the hypothesized effects, we add the general preference for reading *negative information first* as a control construct. All constructs are depicted in the conceptual model in Figure 1. In summary, the conceptual model and hypotheses resulted in a 2 (utilitarian vs. hedonic product) x 3 (screening vs. filtering vs. evaluation phase) x 2 (negative information first vs. later) factorial design.

3.3. Research method

This section describes the survey research method, which products were selected for empirical investigation, how the survey instrument was designed, and how data was collected. When discussing the research method, we decided to conduct a survey study in favor of an experimental research approach, for the following reasons: In both settings, users would be situated in a product search scenario, either on paper or with the help of a prototype. We feared, however, that in an experimental approach with a prototype some participants might click on negative filters only out of curiosity while others might just ignore them because negative filters are still quite uncommon in online search processes. Thus, the observed search behavior might have been biased towards participants' degree of curiosity, which does not occur in a survey study. Furthermore, mockups and prototypes bear the risk of priming participants towards certain design solutions. Hence, we decided to conduct a survey study.

3.2.1. Survey instrument. The consumers' need of negative PUGC in the search process cannot be assessed without setting it into relation with the need for positive PUGC. Of course, consumers would like to see negative information if it was available without opportunity costs. But the space for information presentation is limited, and also attention and time of consumers are limited. So, the need for information should be assessed in a competitive setting, that is, the importance of negative information in comparison to positive information.

Several methods exist to collect data about the relative importance of two options. A simple way would be to use Likert scales, which are generally suitable to assess user perceptions [43] and let the survey participant freely choose the importance for each information type, negative and positive. In the end, both assessments can be set into relation. Another way – comparative scaling with constant sum – is to include the resource limitation directly into the question, by forcing participants to choose from a virtual budget, that is, how many negative product features they want to see out of a fixed amount. This approach allows for better discrimination among options without taking too much time [44]. With only two options (negative and positive product features) and a sum of 10 product features, we consider this method to be easy and understandable for participants.

Regarding the phases of the purchase funnel process, we put survey participants into three different scenarios (i.e., screening, filtering, and evaluation). First, they were introduced to the fictitious scenario of a product search and to the three purchase phases including illustrative examples. This should help participants to obtain a good understanding of the context, although they had to read some text. For each purchase phase, participants received a detailed description of the assessment situation.

Regarding product types, we use the specific examples of a laptop (utilitarian product) and a movie (hedonic product). We chose these two products, as we can assume that everyone has at least once in his life considered buying them and is familiar with the situation to search for those products. For each product type and each phase, participants were given examples of product features (like in Figure 2).

Participants were asked to state the share of negative information (out of all information) they would like to see on a scale from 0 to 10 for each combination of product type and purchase phase, resulting in six survey items. The sequence of survey items was randomized across participants. The questions we asked for each product type are depicted in Table 1. Further, participants were asked to indicate their gender and age and if they read negative reviews first when shopping online.

3.2.2. Data collection and analysis. The survey was implemented as an online survey to be sent out to participants electronically. The hypothesized effects of product type and closeness to checkout as well as the controlled effect of general preference to consume negative information first were assessed by an analysis of variance (three-way ANOVA) and Wilcoxon rank sum tests or Friedman rank sum tests [45] for group differences. The analysis was supported by visual inspection of box and density plots.

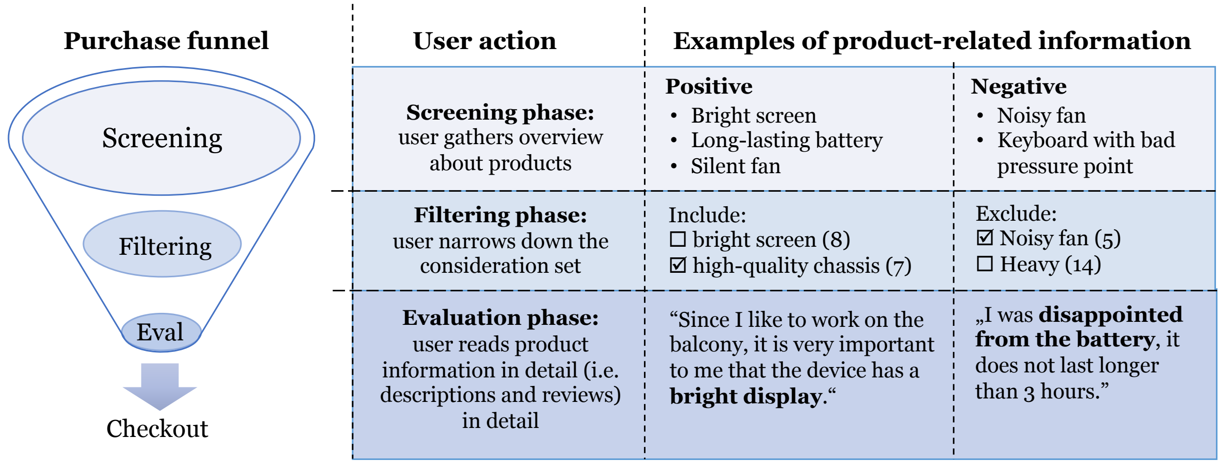

Figure 2. Purchase funnel and examples of product-related information in each phase

Table 1. Descriptive statistics

Sample size	n	148
Screening/Laptop: If only 10 features could be displayed, how many negative product features would you want to see?	Mean	4.196
	Median	4
Screening/Movie: If only 10 features could be displayed, how many negative product features would you want to see?	Mean	3.655
	Median	3
Filtering/Laptop: If you could only set 10 filters for product features, how many of these filters should be negative filters?	Mean	4.027
	Median	4
Filtering/Movie: If you could only set 10 filters for product features, how many of these filters should be negative filters?	Mean	3.486
	Median	3
Evaluation/Laptop: If only 10 reviews could be displayed, how many reviews with rather negatively mentioned product features would you want to see?	Mean	4.466
	Median	5
Evaluation/Movie: If only 10 reviews could be displayed, how many reviews with rather negatively mentioned product features would you want to see?	Mean	3.797
	Median	4
When searching online for products, I read negative reviews first.	Yes	87
	No	61
Age	Min	17.00
	Mean	23.13
	Median	21.00
	Max	50.00
Gender	male	120
	female	28

Table 2. Results of ANOVA and tests for group differences

	ANOVA					Group differences		
	Df	Sum of Squares	Mean Square	F	Sig.	Test type	Test statistic	Sig.
Product type	1	75.5	75.542	19.743	.0000	Wilcoxon rank sum, paired	W=4611	.0000
Closeness to check-out (purchase phase)	2	20.9	10.440	2.7286	.0659	Friedman rank sum	X^2=4.484	.1062
Preference for neg. information first	1	35.4	35.449	9.2646	.0024	Wilcoxon rank sum, unpaired	W=3123.5	.0025
Closeness to checkout X Product type	2	.8	.407	.1062	.8992			

4. Results

In November 2017, the survey was distributed online and sent out to students of three courses at two German universities, one undergraduate (approximately 140 students) and two graduate courses (approximately 50 students and 30 students, respectively). Students were asked to answer the questionnaire at home using their laptops, smartphones, or tablets. 148 students participated in the survey, which equals a response rate of approximately 67%. Owing to the large share of male students in the university's Information Systems programme, from which we obtained most of the answers, our sample was unbalanced in terms of gender (120 male and 28 female, which equals 81% and 19%, respectively). Figure 3 provides a breakdown of respondents' age and gender.

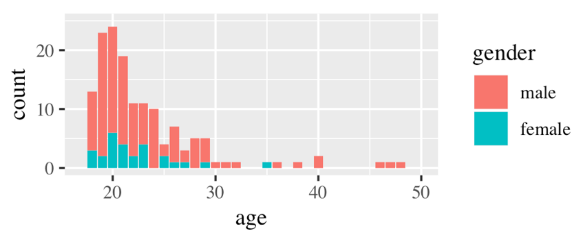

Figure 3. Breakdown of age and gender

Table 2 reports the quantitative results of the statistical analysis. With respect to the effect of product type on need for negative product-related information (H1), survey results confirmed the first hypothesis. The need for negative information was significantly higher for the utilitarian product (laptop) than for the hedonic product (movie) (ANOVA: F=19.7431, p=.0000; Wilcoxon: W=4611, p=.0000).

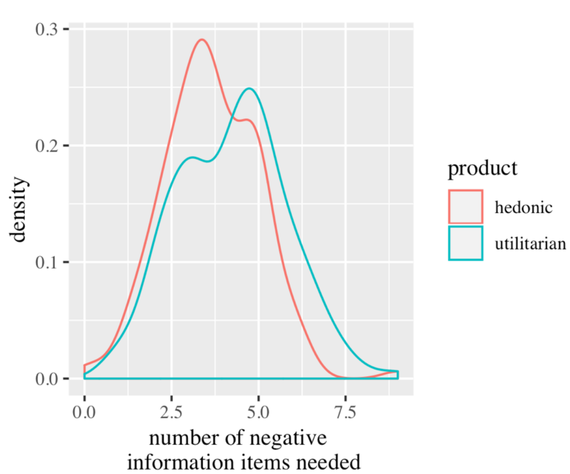

Figure 4. Density plot of the need for negative information for both product types

Figure 4 visualizes the different levels of need for negative information items for the two different product types. We formulate Finding 1:

Finding 1. There is a direct effect of the product type on the need for negative product-related information. A utilitarian product induces a higher need for negative product-related information than a hedonic product. Therefore, H1 holds.

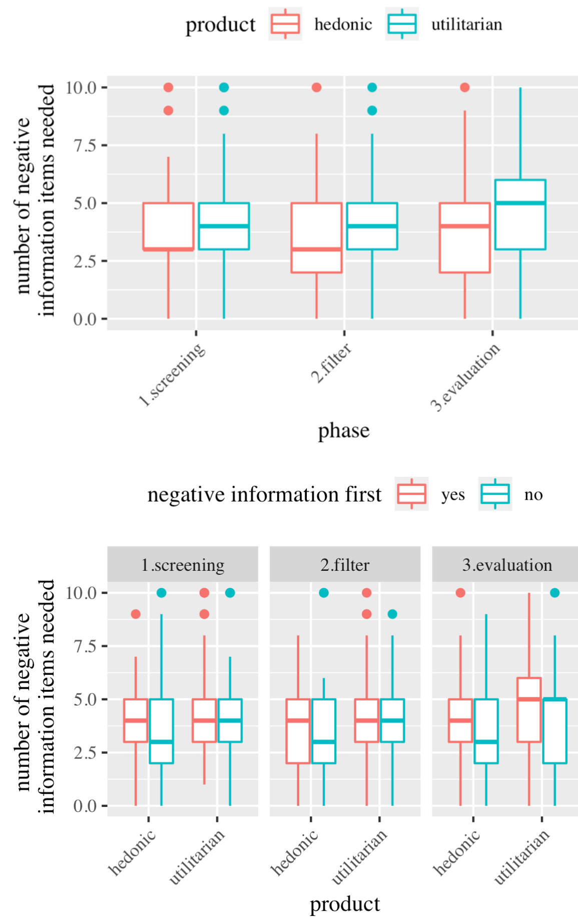

Figure 5. Need for negative information in all three phases a) separated by product type (top) and b) also divided by users' preference to read negative reviews first (bottom)

Moderator effect. The hypothesized moderator effect of closeness to checkout on the effect of product type (H2) was not found to be significant (ANOVA: F=.1062, p=.8992). However, boxplots of data revealed that there is a weak tendency for an interaction of product type and purchase phase as the need for negative information items in the third purchase phase (evaluation) increases slightly stronger for the utilitarian product than for the hedonic product (see Figure 5a). Further, the need for negative information items seems to vary across purchase phases in a non-linear way: For movies, it slightly decreases from phase one (screening) to phase two (filter) and increases from phase two to phase three (evaluation). We summarize Finding 2:

Finding 2. Telling from the statistics, H2 does not hold. Telling from visual exploration, there is at a least a weak interaction of purchase phase and product type with respect to the need for negative product-related information which is, furthermore, non-linear.

The main effect of the purchase phase on the need for negative information was not significant (ANOVA: F=2.7286, p=.0659; Friedman: X 2=4.4848, p=.1062). The control variable of general preference to read negative information first had indeed a significant effect on the need for negative information (ANOVA: F=9.2646, p=.0024; Wilcoxon: W=3123.5, p=.0025). Participants who stated to generally read negative information first also revealed a tendency to seek for more negative information, largely irrespective of the purchase phase (see Figure 5b).

5. Discussion and limitations

Our results indicate that the *need* for negative product-related information depends on the product type. We could confirm that the need for negative product-related information is higher for utilitarian products than for hedonic products. We therefore contribute to negativity bias theory, that not only users' *perception* of negative information, but also their *need* for negative information varies with the product type.

The results provide some interesting insights for ecommerce platform providers on how to enrich a product search with mined product features. Our results show that negative information is important to users as (i) the assessed need for negative product features was almost as large as the need for positive product features, and (ii) 59% of the participants indicated that they read negative reviews first.

It is however interesting to note that the need for negative information does not exceed the need for positive product-related information. In our results, we see that the majority of participants preferred a relatively balanced view on positive and negative information. We speculate that the negativity bias indeed affects human perception of negative information and leads to a biased view–but that it does not lead to a higher need of negative information than positive information. More research is needed to investigate this issue.

Further analyzing the need for negative information, users demand more negative product-related information for utilitarian products in comparison to hedonic products. Our results indicate that users have the strongest need for negative product-related information in the evaluation phase. This seems reasonable because this is the phase in which the final decision in favor of or against a product has to be made. However, this is also the only phase for which participants are familiar with consuming negative information, based on their past shopping experience. Trying to explain the non-significant results regarding the second hypothesis, it might have been that the differentiation between three stages within the survey have not sufficiently represented reality. It is also possible that participants were not sufficiently able to imagine the use of negative information in three different purchase-process phases. One possible reason for this could be that today's ecommerce websites mainly present negative product-related information along with product descriptions at a rather late stage in the purchase process [5] (i.e., the evaluation phase in this paper's terminology). This could mean that participants might not have been able to imagine using negative product-related information in phases other than the evaluation phase. This problem could be overcome in future studies by using mockups or prototypes of (fictitious) ecommerce sites before or during the questionnaire to provide visual examples of how negative product-related information can be integrated into earlier phases. Mockups and prototypes, however, as already mentioned, bear the risk of priming participants towards certain design solutions. Therefore, a survey approach was chosen for this early-stage research on the need for negative information.

The fact that 59% of the participants prefer to read negative reviews first might indicate that the need for negative information differs *within* the phases rather than *across* the phases. For example, in the third phase (evaluation phase) most users prefer to read negative reviews first but want to consume positive reviews later as well. This indicates that there is a sequence dependency of negative and positive information within the phases.

Such sequence effects within a phase are probably less important in the first phase (screening phase), as the single goal of this phase is to obtain an overview of product features and there is hardly any interaction within the phase. In the second phase (filtering phase) however, sequence effects might be interesting, that is, the sequence in which users would want to use positive and negative filters. The third phase (evaluation phase) is the only phase that users have experience with and therefore results for this phase are a strong indication that sequence effects *within* the phases should be further investigated. To address sequence effects *within* the phases, it would be appropriate to investigate the consumption sequence of positive and negative information with a functional prototype and further research can implement such a prototype by drawing on the results we obtained.

Beneath the issues just addressed, we have further limitations. First, the sampling was imbalanced in terms of gender and age. This was owed to the large fraction of male students in the Information Systems programme. However, we see no indication that female users would assess negative PUGC differently from male users. Second, the chosen products were just examples and examples always have specific characteristics that are debatable. Third, there may be a cultural predisposition towards a purchasing process that emphasizes negative product-related information more strongly in the purchasing process than in other cultures. All three limitations, unbalanced sampling product selection, and cultural background, might have biased the results.

6. Conclusion and further research

Insights about a dynamic perspective of the need for negative product-related information can inform ecommerce platform providers on how to design product search in new ways. As a practical implication, web shops and ecommerce platforms which mainly sell utilitarian products should therefore be aware that it might be beneficiary to integrate negative product-related information into the search options and help users discover the negative product-related information in the purchase process. Negative product-related information should be presented on (almost) equal footing with positive product-related information.

This study's aim was to improve the understanding of which information is needed for which product type in which phase of the purchase process. Especially, the need for negative product-related information has potential to enrich product search significantly. Future ecommerce sites increasingly face the challenge to process and organize user-generated content in a meaningful and effective way. By gaining more knowledge about information needs, web shop managers will better be able to design product search experiences and satisfy the information need of customers. While research on the negativity bias has been agnostic of purchase-decision process phases so far, we combined the concepts of negativity effects and decision phases to analyze information needs in a dynamic way.

With the knowledge of users' needs for negative product-related information throughout the purchase-decision process comes the potential to design the purchase process more efficiently. However, measuring the quality of the purchase process itself (e.g., with well-known metrics, like a consideration set, time consumed, or quality of the decision) needs further research, for which our findings may serve as a basis. Further research could (i) investigate on more aspects of information need in early phases of the purchase process, (ii) take more product type classifications into consideration, (iii) conduct the study with different types of user communities, or (iv) investigate the effects of negative product-related information on purchase intention and conversion rate.

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