

Impact of Review Tag Function on Perceived Biases of Consumers – An Examination Using Attribution Theory

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Abstract

Since online reviews have become an increasingly important information source for consumers to evaluate products during online shopping, many platforms started to adopt review mechanisms to maximize the value of such massive reviews. In recent years, review tag function has been very popular in practices and leading the research on sentiment and opinion extraction techniques. However, the examination of how the function works has been largely overlooked. In this paper, we specifically look into the impact of the tag function on positivity and negativity biases by proposing a framework through the lens of attribution theory. We also put forward an experiment design to test our hypotheses. Our research intends to fill in the research gap of review tag function and offer new perspective to understand its impact on the consumers. Potential contribution and limitation of this research will be discussed in the proposal.

Keywords: Online reviews, Review tag, Perceived bias, Attribution theory, Electronic commerce

1. Introduction

Online product reviews are peer-generated product evaluations posted on company or third party websites (Mudambi and Schuff 2010). As reviews bring great value in reducing information asymmetry of online markets (Dellarocas 2003), research on product reviews has been a hot topic in IS discipline during the past decade. One of the most intensive discussion is on the positivity/negativity bias brought by product review ratings (Bao and Chau 2016a). On one hand, prior research has discovered that negative reviews are more likely to be perceived helpful, namely negativity bias (Kuan et al. 2015; Sen and Lerman 2007). On the other hand, some empirical studies also found the existence of positivity bias (Pan and Zhang 2011), that positive reviews are considered more helpful. The examination on biases is important to understand consumers' cognitive processing of reviews. However, in between the contradictory opinions, the power of review's textual content has been largely disregarded.

Without a doubt, review texts could be massive. To help consumers understand products more easily in such situation, many text-mining techniques have been developed in prior research, such as automatic review summarization (Blair-Goldensohn et al. 2008; Zhuang et al. 2006), feature-based search system (Scaffidi et al. 2007), review ranking system (Ghose and Ipeiritis 2007), comprehensive review set selection (Tsaparas et al. 2011) and so on. In current practices, many platforms have started their trials on using such techniques. For instance, both TripAdvisor.com and Taobao.com have adopted review tag functions to present the most frequently mentioned review content on top of all the reviews. While TripAdvisor merely shows the tag label (shown in Figure 1),

i.e. the most frequent features that people comment on, Taobao displays the tag labels as well as the corresponding sentiment using different colors (shown in Figure 2).

The review tag function is mostly used for popular products (Hu and Liu 2004), because under such situations, reviews are too numerous to be processed by human in an effective way. The adoption of the technique could be beneficial for both buyers, sellers and platforms. Buyers are enabled to save their search costs before making an informed decision; sellers could keep track and manage the customer opinions (Hu and Liu 2004). Meanwhile, platforms can also benefit from the better experience they brought to the other parties.

With the techniques being extensively studied in the domain of computer science, few research studies in IS discipline targeted on investigating the phenomenon. To fill in the research gap, this paper attempts to reveal the impact of tag function through the lens of attribution theory. More specifically, we ask the question: how does review tag function influence negativity or positivity bias? Does it strengthen or weaken one of the biases? By putting forward a research design, the proposal aims to contribute to online review studies and extend the current discussions on consumer biases. The results and findings of the proposal could also bring insights from both theoretical and practical perspectives.

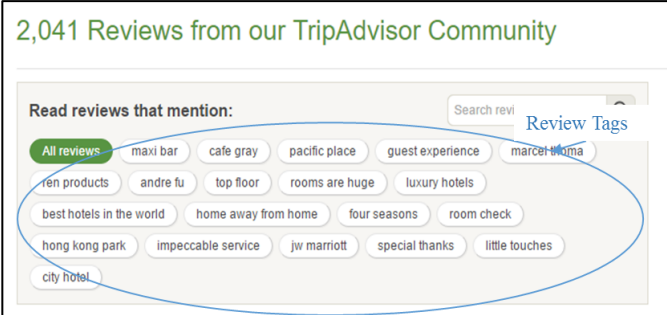


Figure 1. Review tag function on TripAdvisor.com



Figure 2. Review tag function on Taobao.com

2. Theory Background

2.1 Review Tag Function

Before we bring up the theoretical foundation, we introduce the review tag function in more details. We take the current tag function on Taobao.com as our target prototype.

A simple version of tag-generating tool has been described in the work of Archak et al. (2011). Review tags are generated by summarizing all the review texts. The process includes and is not limited to feature extraction, sentiment classification and text summarization (Hu and Liu 2004). As a result, a set of noun phrases and the respective sentiment are produced, which corresponds to

product features and their evaluation. Current practice in Taobao.com limits the total number of review tags to ten, so that the function at most displays the top ten features and their sentiment according to the feature frequency ranking. On Taobao.com, the positive tags are presented in red color and negative tags are in green color. Both types of tags display the frequency of the features being mentioned in reviews.

As shown in prior literature, for most products, the number of positive reviews are much larger than that of negative reviews (Dellarocas 2003; Hu et al. 2016). To understand the tag function in the most common situation, in our research, we assume that product reviews follow the J-shape distribution, which is positively skewed, asymmetric and bimodal (Hu et al., 2016). Therefore, such as shown in Figure 2, for a review system with tag function, there are fewer negative tags than positive tags in a typical setting. Moreover, because of the low frequency of negative reviews, negative tags are often placed after positive tags.

2.2 Attribution Theory

Attribution theory was developed in the field of social psychology for understanding how people perceive and evaluate the behaviors of others (Heider 1958). Attribution refers to the perception or the inference of cause. Attribution research is concerned with all aspects of causal inferences.

There are three pre-assumptions in the theory (Försterling 1986). The first one is that people interpret behavior in terms of its causes and that these interpretations play an important role in determining reactions to the behavior (Heider 1958; Kelley and Michela 1980). The second assumption is that people are generally motivated to gain a realistic understanding of the causes that have led to different events in their personal domain (Heider 1958). Third, it is assumed that a causal understanding serves the function of attaining personal goals and survival (Kelley 1987).

At first, when Heider proposed the attribution theory in his book (Heider 1958), he distinguished causes of actions into two basic types, personal or internal causes, and situational or external causes. For example, if Tom recommends a movie to others, his action might due to his internal taste for this movie, or to other external factors, e.g. every audience of the movie on that day is given a voucher.

Later, Kelley extended and elaborated on how individuals infer causes (Kelley 1967; Kelley 1973). According to his topology of person–stimulus–circumstances, general attributions could be made to the person (Tom’s taste for the movie), the stimulus (the movie quality), and circumstances (special gifts for the audiences). Information is used to facilitate an observer’s attribution of a behavior.

Kelley (1973) proposed the principle that when people make attribution to an actor’s behavior, they would take into consideration how others behave in the same situation. The term, consensus information, is used to refer to the way in which other people respond to the stimulus. Take Tom’s recommending the movie as an example, if everyone who watched the movie recommends it, we would observe high consensus. When most others behave in a similar way to Tom, i.e. there is high consensus, we, as observers, tend to attribute the causes external to Tom. But as consensus decreases, our attribution would be more internal to him (McGill 1989).

The theoretical development of attribution theory had enabled consumer research to explore a variety of studies, specifically, the research line which examines the process by which individuals assign causal agency to outcomes experienced by others (He and Bond 2015).

3. Hypotheses Development

Our context of online reviews readily fits the principle proposed by Kelley. When making purchase decision, individuals would observe others' product experience contained in reviews. When processing the review information, they would attribute the review content to either product-related features or reviewers' characteristics.

There have been studies using attribution theory within the context. For example, Chen and Lurie (2013) studies the effect of temporary contiguity on reviews' causal attribution. They found that when reviews' writing closely follows consumption, positive reviews would be more attributed to products and hence be more valued. In examining the review dispersion, He and Bond (2015) found that consumers taste similarity moderates the relationship between review dispersion and the attribution to reviewers.

For review system with tag function, potential consumers can read the summarized tags extracted from product reviews. Each of the tags represents a set of product-related features and the respective sentiment, either positive or negative. The presence of tags eliminates consumers' efforts in processing and extracting the outstanding features. However, on the other hand, it might also restrict the scope of features from which consumers make attributions and hence evaluate the product.

Since review tags demonstrate the most frequent feature evaluation, they can also be regarded as high consensus information. According to the attribution theory, the consensus information affords a basis for confidence in one's judgment (Kelley 1973). For positive tags, when potential consumers find that most others respond positively to the same product, they may tend to attribute the positive evaluation to product-related causes. Therefore, the positive reviews would be perceived more valuable and hence positivity bias could be enhanced.

However, for negative tags, since the evaluation frequency comes much less than positive evaluation frequency, negative tags tend to be comparatively viewed as low consensus information. As a consequence, the negative evaluation contained in negative tags is more likely to be attributed internal to reviewers and hence perceived less useful in identifying the product. Therefore, the negative bias could be mitigated. We hypothesize that,

Hypothesis 1. Consumers are more likely to perceive positive reviews as helpful when using review system with (*vs* without) tag function.

Hypothesis 2. Consumers are less likely to perceive negative reviews as helpful when using review system with (*vs* without) tag function.

4. Methodology

We plan to conduct a between-subjects online experiment to test our hypotheses. First, we will collect product, review and tag data on Taobao.com. We will select multiple products as people might comprehend product information differently for different products (Bao and Chau 2016b). We will use criteria of review volume and distribution to ensure representative review settings. Second, we plan to modify the data and create mock product pages. For a product, we will prepare two webpage versions, one with tag function and one without, while keeping every other element being equal. Although the tag function is mostly used for popular products, which might possess hundreds or thousands of reviews, yet in the experiment, to control for the potential effect of review volume, we

constrain the number of reviews to 100, so that potential customers could be able to browse all the content within several pages in both versions.

Next, we would design our survey questionnaire to collect subjective data. Then, we will recruit participants to browse the mock page and ask them to respond to our survey afterwards. Meanwhile, we will also collect the click stream data of the participants as support to our research hypotheses. Analyses on both subjective data and click stream data will be made in a later stage.

5. Potential Contributions and Limitations

5.1 Potential Contribution

Our research has the following potential contributions. First, it fills in the research gap of investigating the impact of review tag function. Second, our research adds value to the current understanding of consumers' cognitive biases during review consumption. Also, our findings have the potential of extending the attribution theory and its applicable domain. At last, our research might be beneficial to practices of tag function in online markets by illustrating its impact on consumer perceptions.

5.2 Limitations

Our proposal has several limitations. First, our target prototype is the review tag function on Taobao.com, which might induce questions of generalizability due to the cultural and language differences. Second, our research assumes a J-shape distribution of reviews for a given product, so the same queries on other review distribution settings might be raised. Besides, the selection of positive and negative features might also influence answers to the research question. Future research could draw on review distribution or selected features to explore their roles in affecting consumers' perception.

Acknowledgment

This research is supported in part by the General Research Fund from the Hong Kong Research Grants Council (#17514516B) and the Seed Funding for Basic Research from the University of Hong Kong (#104003314).

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