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When Do Likes Create Bias?

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Emergent Research Forum (ERF)

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Abstract

The rise of online communities has ushered in a new era of content sharing with platforms that serve many functions and overcome the geographic and synchronous limitations of traditional word-of-mouth communications. Community-based question answering sites (CQA) have emerged as convenient platforms for users to exchange knowledge and opinions with others. Research on CQA has primarily focused on engaging members to voluntarily contribute to these communities. Helpfulness ratings and "likes" are one mechanism platforms can use to engage members, but these subjective evaluations can also create bias. In this ERF paper, the elaboration likelihood model is applied to better understand when bias can occur with these platforms. An experimental design and a planned data collection are reported.

Keywords

Cognitive bias, elaboration likelihood model, number of "likes", topic relevance, question answering sites

Introduction

The rise of online communities has ushered in a new era of content sharing. As a result, multiple applications have emerged, such as blogs, online product reviews, wiki applications and question answering sites (Chen et al. 2011). These online opinion-sharing platforms serve many functions and overcome the geographic and synchronous limitations of traditional word-of-mouth communications (Faraj et al. 2015). Among them, community-based question answering sites (CQA), named by Lee et al. (2019), serve a large number of users, and several popular CQAs such as Quora, Yahoo! Answers, and Stack Exchange have emerged as convenient platforms for users to exchange knowledge. Since the success of these CQAs depends on users' active engagement (Kuang et al. 2019), researchers have begun to study the motivation or incentives that engage and activate participants (Khansa et al. 2015, Kuang et al. 2019).

In CQAs, one of the most popular mechanisms for engaging community members is to enable them to express their opinion of the content (Lee et al. 2019), often referred to as *ratings* or "*likes*". Specifically, community members are provided with a mechanism to rate CQA content quality through voting up or down, or by assigning numerical ratings. These subjective assessments of content quality can hold great influence with community members but can also be a source of cognitive bias. In this CQA context, cognitive bias is viewed as a systematic deviation from a normative standard (e.g., Adomavicius et al. 2019; Kahneman et al. 1982). Researchers have shown that in the information-abundant online environment, heuristic processing is more likely to be adopted due to information overload (Metzger et al. 2010) and heuristics can result in cognitive bias. While the *number of "likes"*, the result of subjective voting, may help to attract the attention of online readers (Kuan et al. 2015; Lin et al. 2019; Li & Hitt 2010), research suggests that such cues may also bias readers prior to assessing the objective quality of answers (Lee et al. 2019).

Since objectivity is essential in question asking platforms, cognitive biases can lead to potential problems. Given that topics in CQAs are often relevant to social topics or individual beliefs, this bias could influence readers in a profound way. Also, the biased display of answers may potentially contaminate the effectiveness of the platform (Adomavicius et al. 2013, 2019; Lee et al. 2019), causing readers to lose confidence in the platform and visit less frequently.

Based on the availability of both central arguments (i.e., opinions) and peripheral heuristic cues (i.e., "likes"), we adopt an information-processing perspective and employ the Elaboration Likelihood Model (Petty & Cacioppo 1986) to examine how readers process information in this information-rich environment (Liu & Karahanna 2017). Specifically, we consider the following research questions: (1) does number of “likes” bias readers in online opinion sharing platforms, and (2) under what conditions are users more easily biased. An experimental design is developed to examine these research questions.

In the following sections, the literature on community-based question answering sites (CQA), and other relevant online opinion-sharing sites, is reviewed. The theoretical foundation for this research, the Elaboration Likelihood Model, is then introduced and described in the context of CQA. Next, the experimental design for the study is presented, a 3x2x2, within-subjects design with “likes” (high, low, none); argument quality (high, low) and topic relevance (high, low). The experimental treatments and measurement scales are described. Last, the planned research and data collection is discussed. Our research aims at raising community awareness that the most-liked answers may not be reliable, and that platforms should consider additional ranking strategies, in addition to the number of “likes”.

Literature Review and Theory

Online opinion platform, or review systems, are defined as IT-enabled information systems “where individuals exchange experiences and opinions on a variety of topics ranging from products and services, to politics and world events” (Piccoli 2016). Community-based question and answer sites (CQA) are a popular form of opinion sharing platform, on which users can post questions or provide answers to others’ questions. IS research has examined these and other online communities, focusing on user motivations, such as why individuals use these tools (Simeonova 2018), sharing knowledge and helping strangers in these online communities (Chai et al. 2011; Huang et al. 2011; Wasko & Faraj 2005). IS scholars have also focused on the different user roles, examining why some act as leaders (Faraj et al. 2015), and others exhibit aggressive behavior online (Xu et al. 2016). Other scholars have examined the quality of information in online communities, including how community diversity, conflict management, moderation systems, and balanced groups can contribute to better information quality (Chen et al. 2011).

While many features of these online communities can enhance knowledge sharing, increase community involvement, and motivation to contribute, there is also potential for low quality information and bias. Researchers have noted that online users, in general, heuristically determine the credibility of information based on others’ evaluations (e.g., Metzger et al. 2010). Concerns about “bias” in users' information processing are not new, and in fact, are common due to users’ cognitive limitations when using information systems. In online review platforms, researchers have found that ratings can serve as a valuable anchor for users (e.g., Adomavicius et al. 2019), but there have also been several studies on cognitive bias with such platforms (Li & Hitt 2010; Kuan et al. 2015; Yin et al. 2016).

While these voluntary voting mechanisms are helpful in contexts such as online product reviews (Kuan et al. 2015), these mechanisms may play a more important role in CQA platforms. In CQA platforms, only the opinions (reviews) receive ratings, whereas in online product review platforms, both products and reviews receive ratings. Also, the bias and lack of objectivity that may result from “likes” may have greater impact with CQA platforms due to the nature of the topics, which are often social and personal issues. Concerns about bias in CQA platforms have recently been noted, and “Best Answer” designations have been cited as poor sources of information for these communities, while the use of “likes” is recommended (Lee et al. 2019). More research is needed on rating systems which may encourage participation from community members, but also create bias and dissatisfaction with information quality on the platform.

Given the existence of opinions (arguments) that require central processing, and “likes” or ratings that are evaluated with peripheral processing, we adopt the elaboration likelihood model (Petty and Cacioppo 1986) for theoretical insight on how opinions and “likes” can influence information processing, persuasion and bias in CQAs.

Elaboration Likelihood Model

Petty’s elaboration likelihood model (ELM) (Petty & Cacioppo 1986) is commonly applied by researchers examining cognitive reasoning topics. ELM describes how persuasion can occur through two major routes: a central route and a peripheral route, with more cognitive effort being expended to process a message with the central route as compared to the peripheral route. When people use the central route, they are persuaded through systematic reasoning, i.e. considering the quality of arguments. In contrast, if people use the peripheral route, they are persuaded with simple heuristic cues, which are extrinsic to the argument content. Bias can occur when people use the peripheral route, as less systematic reasoning is used, and decisions are based primarily on cues which may be unrelated to argument quality. ELM provides a theoretical framework which can account for a person's motivation and ability, the strength of the message, the expertise of the message source, and context variables.

Figure 1 below presents the ELM model with main and moderating effects (Petty & Cacioppo 1986) as applied to the current study context, with the central route using opinions (strong/weak) on a CQA site, and the peripheral route using cues in the form of "likes" (high, low, none) on a CQA site. Both the central route and the peripheral route (main effects) are hypothesized to influence attitude change and persuasion. The moderating role of motivation and ability are operationalized with topic relevance (high/low). Specifically, when the reader is motivated, i.e. when a topic is highly relevant, central cues will dominate any attitude change. Whereas, when a topic is less relevant, people have lower motivation and ability to engage in issue-relevant thinking, and peripheral cues will dominate any attitude change. In this model, the expertise of the source (i.e., the "likes" generated by the community) and the characteristics of the message (all messages have a positive valence) are controlled.

Based on the ELM model, we propose four hypotheses:
H1: *The number of "likes" is positively associated with argument persuasion.*
H2: *The argument quality is positively associated with argument persuasion.*
H3: *Topic relevance moderates the relationship between number of "likes" and argument persuasion, such that the relationship is stronger when the topic relevance is low.*
H4: *Topic relevance moderates the relationship between argument quality and argument persuasion, such that the relationship is stronger when the topic relevance is high.*

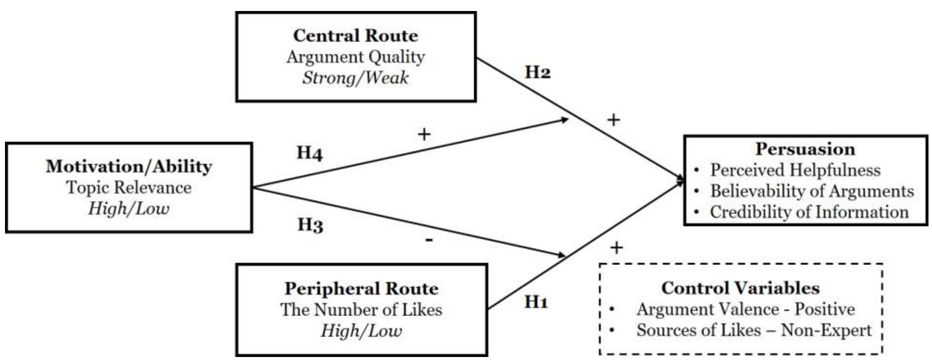

Figure 1. Research Model

Research Design

A 3 × 2 × 2 within-subjects research design, with number of "likes" (high, low, none), argument quality (strong, weak) and relevance (high, low), will be employed to test the hypotheses. Number of "likes" will be operationalized at high by randomly selecting a number between 600-900, while the low number of "likes" will use a number randomly selected between 1-10. Based on Toulmin's Model (Kim & Benbasat 2006), two levels of argument quality, strong and weak, were developed. The strong arguments include a claim (a brief statement of opinion), and also include data (evidence supporting the claim) and backing (evidence explaining why the data should be accepted) (Kim & Benbasat 2006). Weak arguments provide only a claim, with no evidence or backing. The claims were formulated based on real data found online. High and low topic relevance were also specified after some initial pre-testing. Six real-world topics were selected from an online opinion sharing platform, including 3 topics that were estimated to be highly relevant, and 3 topics that were less relevant based on the sample characteristics of undergraduate students in the U.S. Johnson and Eagly's (1989) description of outcome-based and value-based relevance were used to select the final pair of high/low relevant topics. Table 1 provides the complete set of treatments for the high relevance condition (*Should I encourage my friend's "unrealistic" dream?*). Due to space constraints, the low relevance topic treatments (*Should EU reform farm policy as New Zealand* *did?*) are not included.

Persuasion will be measured using three, 7-point Likert-type scales (How believable do you find this argument? How helpful do you find this argument? How credible do you find this argument?) (Petty & Cacioppo 1986; Metzger et al. 2010). Based on the existing literature, the valence of the argument (Yin et al. 2016), and source expertise (Kim et al. 2019) were identified as antecedents to persuasion, and possible confounding variables. Thus, these variables were controlled, and only positively-valence arguments were used in the treatments, and the experimental instructions state that the "likes" were posted from the community crowd, and not by experts.

Weak	Strong
I will encourage my friend's "unrealistic" dream. It's not my place to decide what is a realistic goal.	*I will encourage my friend's "unrealistic" dream. It's not my place to decide what is a realistic goal.* My idea of what is realistic is inherently limited by my own life experience. Becoming an astronaut or being elected president or finding a cure for cancer are goals that most people don't achieve. Yet there are people out there became astronauts and presidents.
My friend should be encouraged. The process of pursuing a dream is valuable.	*My friend should be encouraged. The process of pursuing a dream is valuable.* When they are living the dream, they are driven to grow what they have and make it better. Even if they eventually fail the goal or change their minds of dreams, they will at least acquire valuable experiences of how to be concentrated and effective, how to manage time and how to live with disappointments etc. Those soft skills will be extremely helpful when they pursue other goals.
I prefer to encourage the "unrealistic" dream. I don't want to lower my friend's expectations.	*I prefer to encourage the "unrealistic" dream. I don't want to lower my friend's expectations.* I didn't need someone to lower my expectations for me, and on reflection, it can discourage a friend from doing their best. Eventually, they may become interested in other things, but they will not lose desire to try achieving goals.
Yes, I will encourage my friends and ask them to have back-up plans.	*Yes, I will encourage my friends and ask them to have back-up plans.* They might become what they want to be but find themselves don't like it any longer. So, having the back-up plan of other interests could help them be less passive.
I will encourage my friend but also make them aware that things don't always turn out the way we want.	*I will encourage my friend but also make them aware that things don't always turn out the way we want.* For example, if she wants to be an actress, I will let her know how many people try for it and end up as waitress. If she still decides to pursue the dream after knowing the underling risks, I will definitely support her.
I will not crush my friend's dream. I will tell her "you can be any-thing you want to be."	*I will not crush my friend's dream. I will tell her "you can be anything you want to be."* She may not succeed in this goal or change her career, but she will have confidence that she can do whatever she wants to do. This will serve her well in any position.

Table 1. Argument quality, High-relevance topic: Encourage friend's "unrealistic" dreams

Experimental Procedure

The participants will first complete a pre-survey that contains demographic questions, and then will complete a 15-minute experimental task in which they will be asked to review questions and answers in a CQA style interface. Participants will review questions for 2 different topics (high and low relevance), and for each topic, they will be presented with 3 answers (with high, low and no "likes"). The assignment of strong and weak answers (i.e., arguments) to each topic will be randomized, as will the assignment of "likes" to arguments. The order of presentation of questions (topics) and answers (arguments) will be counter-balanced across subjects. After reading each answer (argument), participants will be asked to respond to measurement scales on persuasion, and answer manipulation check questions for argument quality, and number of "likes". The manipulation check for topic relevance will be presented right after the question for each topic is presented.

Future Research

Data collection is planned for late spring and thus results from this study should be available for presentation at AMCIS 2020.

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