Available online at www.sciencedirect.com
ScienceDirect
Journal of Interactive Marketing 44 (2018) 17–28
JOURNAL OF INTERACTIVE MARKETING
www.elsevier.com/locate/intmar

How Online Reviews Become Helpful: A Dynamic Perspective☆

Shuya Lu [a] & Jianan Wu [b,]* & Shih-Lun (Allen) Tseng [c]

[a] Louisiana State University, 2114 Business Education Complex, Nicholson Drive Extension, Baton Rouge, LA 70803, United States
[b] Louisiana State University, 2113 Business Education Complex, Nicholson Drive Extension, Baton Rouge, LA 70803, United States
[c] Clemson University, 440 Sirrine Hall, Clemson, SC 29634, United States

Abstract

Online product reviews aid consumer decision making. Although many studies show that review characteristics have salient effects on review helpfulness, little research has investigated whether such effects change temporally. To bridge this research gap, we study the dynamic formation of review helpfulness by considering the behaviors of three major players in a typical review system: consumers, the review hosting firm, and reviewers. This study uses both dynamic and static drivers of review helpfulness to examine temporal changes in their effects on review helpfulness, along two time characteristics of a post: its lifespan and its timing. Daily data collected from Amazon show that for long post lifespans or late post timing, the effects of static drivers and the spillover effect of dynamic drivers weaken, but the carryover effect of dynamic drivers strengthens. For vendors to leverage user reviews of a product, high-quality reviews posted early are extremely important and should be cultivated diligently. Sorting by review quality attributes, such as review length, also can effectively prolong the time window for reviewers to write high-quality detailed reviews.

Keywords: Online reviews; Dynamics; Helpfulness depth; Helpfulness breadth; Helpfulness rank

Introduction

Online user reviews play an important role in helping consumers make purchase decisions. According to a survey, 92% of consumers now read online reviews (Local Consumer Review Survey 2015). Research shows that review helpfulness is driven by review quality attributes (i.e., characteristics of a review that are determined when a review is posted), such as ratings (Goes, Lin, and Yeung 2014; Hu, Koh, and Reddy 2014; Weathers, Swain, and Grover 2015), length (Kuan et al. 2015; Mudambi and Schuff 2010; Schindler and Bickart 2012), and the reviewer's expertise (Cheung, Sia, and Kuan 2012; Weathers, Swain, and Grover 2015; Willemsen et al. 2011). These studies shed light on review quality attributes that significantly affect review helpfulness (Moore 2015; Salehan and Kim 2015; Yin, Bond, and Zhang 2014).

But most studies that address how review quality attributes drive review helpfulness are based on a single snapshot of the review system. The various review measures are observed at a specified time (e.g., Wu 2017) and assumed to be static. Although some of them are static (e.g., rating or length of a review never changes, regardless of when the snapshot is taken), others are dynamic. For example, the percentage of helpful votes changes, depending on when the snapshot of the system is taken. Ultimately, static restrictions make the conceptualization, methodology, and data collection for studies of review helpfulness simpler and more convenient, but they also limit, and may bias, understanding of the dynamic formation of review helpfulness. Review helpfulness formation is not only a consequence of the interplay of multiple involved parties (e.g., consumers, review hosting firm, and reviewers) but also a result of their dynamic interactions.

We use review X (Fig. 1) for an Amazon Kindle Fire HD 10 on Amazon.com as an example to illustrate the temporal effect of a

☆ The authors are thankful for the comments they received in the 2016 ISMS Marketing Science Conference (Shanghai).
* Corresponding author.
E-mail addresses: slu12@lsu.edu (S. Lu), jiananwu@lsu.edu (J. Wu), shihluc@clemson.edu. (S.-L.(A.) Tseng).

https://doi.org/10.1016/j.intmar.2018.05.005
1094-9968

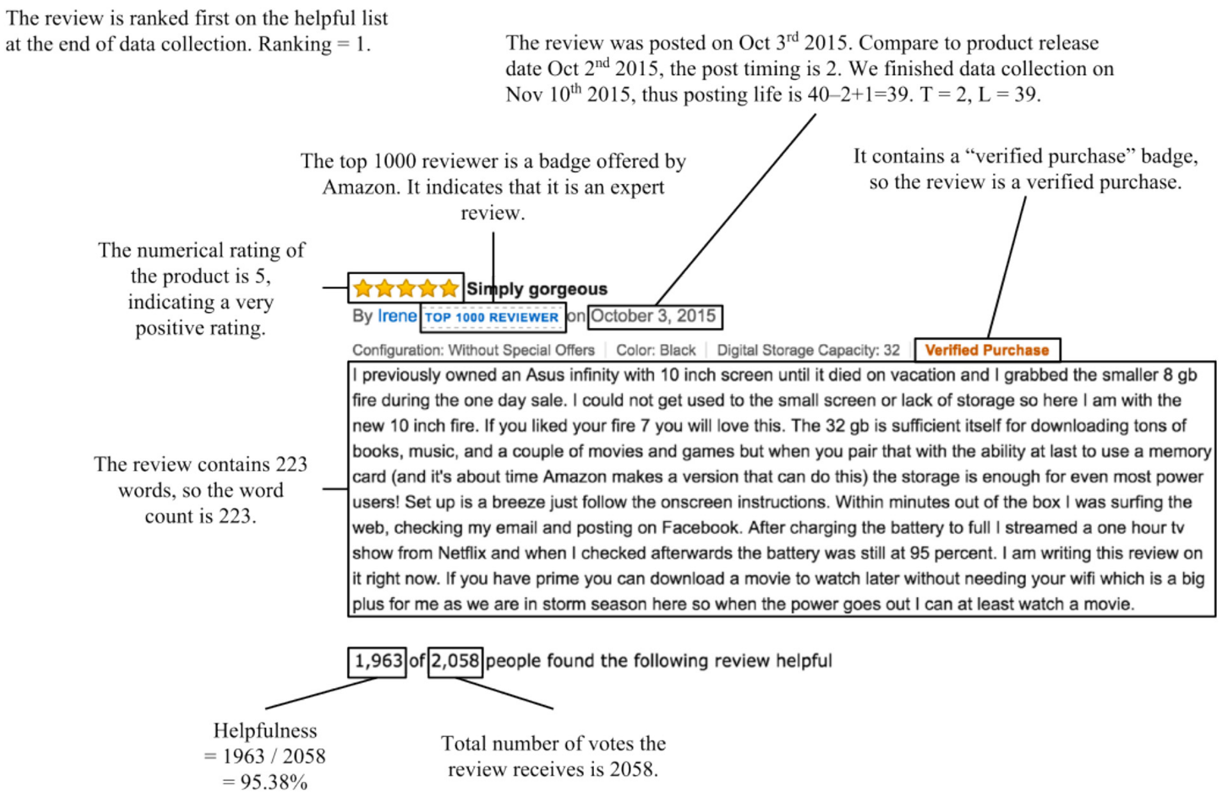

Fig. 1. An example of an online review (review X). Note: This review written by Irene is for the Amazon Kindle Fire HD 10 Tablet. Irene gave the product a five-star rating with 223 words in review text. It is an expert review and a verified purchase. The review is ranked first on the helpful list; thus, ranking is 1. The review received 2,058 total votes with a helpfulness percentage at 1,963/2,058 = 95.38%. The review was posted on October 3, 2015; compared with the product release date (October 2, 2015), the post timing is 2. We finished data collection on November 10, 2015; thus, the review has stayed online for 39 days. In other words, the highest posting life of the review is 40 − 2 + 1 = 39 in our data set.

review characteristic on review helpfulness formation. Review X shows three different time stamps: product released (October 2, 2015), review posted (October 3, 2015), and review observation window (October 3, 2015–November 11, 2015) (Fig. 2). We observed the quality attributes and helpfulness of review X on each day since it was posted, totaling 39 observations.

During the observation window, review X accumulated 2,058 consumer votes, of which 1,963, or 95%, were helpful. It had been the highest ranked review in the most helpful review list of the product at Amazon since the product was released. Fig. 1 shows that review X's helpfulness measures (i.e., helpfulness ranking or percentage of helpfulness voting) formed dynamically throughout its 39-day duration, as its total votes and helpful votes, cast by consumers, were updated, and its ranking on the most helpful list was updated accordingly by Amazon, according to its algorithms.

Current literature implicitly assumes that the quality attributes of a review (e.g., length) have a constant impact on review helpfulness. We argue that this impact varies according to two time measures: (1) how long the review has existed and (2) when the review is posted. For the first measure, the longer a review exists, the weaker its power to influence helpfulness becomes. In other words, the effect of review length on its helpfulness may be strong when the review is initially posted but weakens after it has been posted for a while. This weakening effect may occur because the information (as

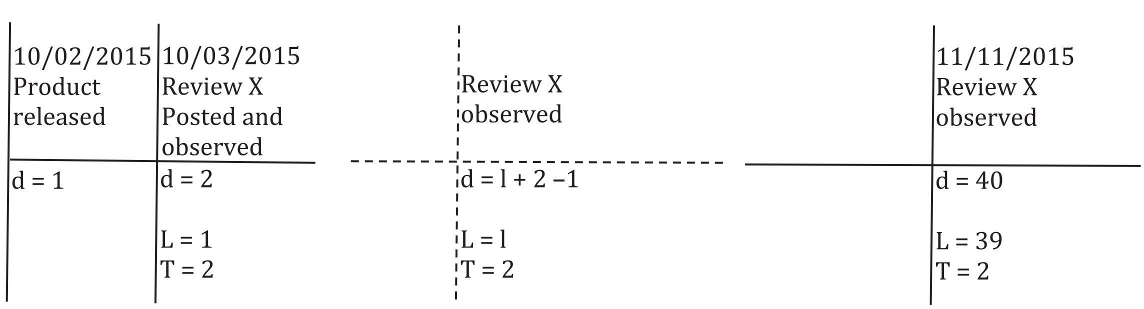

Fig. 2. Time stamps and time measures for review X. Note: The figure provides product release date, review posting date, and review observed date of review X and shows how to use the three time stamps to calculate day d, post lifespan L, and post timing T. We thank an anonymous referee for helping us with this figure.