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Yue Li
Dalian University of Technology, 838050727@qq.com

Huifang Li
Dalian University of Technology, huifangli@dlut.edu.cn

Qingfei Min
Dalian University of Technology, minqf@dlut.edu.cn

Zhiyong Liu
Dalian University of Technology, leoliuzy@dlut.edu.cn

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Research-in-Progress

Yue Li
Dept. of Information Management and Information Systems, Dalian University of Technology
liyue_dut@hotmail.com

Huifang Li
Dept. of Information Management and Information Systems, Dalian University of Technology
huifangli@dlut.edu.cn

Qingfei Min
Dept. of Information Management and Information Systems, Dalian University of Technology
minqf@dlut.edu.cn

Zhiyong Liu
Dept. of Information Management and Information Systems, Dalian University of Technology
leoliuzy@dlut.edu.cn

Abstract

Online review websites play an important role in customer's purchase decision-making process for the useful product knowledge contained in the customer-generated reviews. However, the increasing information volume also makes it difficult for customers to identify and consider those attributes relevant to their decision. Based on Information Processing Theory (IPT) and Multiple Pathway Anchoring and Adjustment Model (MPAAM), we proposed three characteristics of online reviews affecting review helpfulness (e.g., attractiveness, representational sufficiency and functional sufficiency) and examined the moderating influences of information volume on these relationships. A large-scale review dataset from Yelp.com are collected and text analysis technique are applied to validate our research model. Our work, which illustrates the disturbance effect of information volume, has implications for both online word-of-mouth and information processing research.

Keywords: Online review sites, review helpfulness, review characteristics, information processing

Introduction

Online review sites like Yelp.com and Dianping.com are playing important roles in both supporting consumers' evaluation of businesses and their products and providing referral traffics for businesses (Liu and Karahanna 2017). For instance, about 74% of the consumers searching online for a local business turn to online review sites at least once a month (Belt 2017). However, the gathering of massive information in the online review sites also makes consumers be confronted with challenges. For instance, irrelevant information may gratuitously expend consumers' cognitive resources (Goswami 2015); proxy indicators sometimes provide unilateral information and mislead consumers (Fei et al. 2017; Sen and Lerman 2007); and information conflict about attribute-level product performance leads to swaying effects (Liu and Karahanna 2017). Thus, it's important for the businesses in the online review sites and the providers of the sites to figure out an efficient way of constructing reviews to increase review helpfulness, which denotes the extent to which an online review helps consumers with the purchase decisions-making processes.

A systematic review of studies on online reviews suggest that extant literature has under-explored the review characteristics regarding different stages of consumers' information processing, the role of these characteristics and information volume in affecting review helpfulness. To be specific, first, most extant studies explore review helpfulness from diagnosticity-comprehension perspectives, but few have considered the way of a reviews gets into consumers' sights before being comprehending; second, although prior studies considering the influences of review characteristics yield rich implications for the practice of businesses and online review sites providers, the role of information volume is not elaborated. Third, we extract variables from both web-providing indicators and text content to validate our theoretical hypothesis. Hence, the objective of this study is to investigate the following research questions: *(1) What are the review characteristics that impact review helpfulness in the information processing process? (2) How do these characteristics influence review helpfulness? (3) How does information volume moderate these relationships?*

To address the research questions, we first identify review information attributes that impact review helpfulness in online review websites by drawing on information processing theory (IPT) and multiple pathway anchoring and adjustment model (MPAAM) (e.g., attractiveness, representative sufficiency, functional sufficiency); We then theorized the moderating influence of information volume on these relationships; Finally, we empirically validated the relationships by collecting a large scale of review dataset from Yelp.com and creatively deploying sentiment analyzing technique.

Theory and Hypotheses

Prior studies explore online review helpfulness from two main theory streams: (1) Communication theories explain what kinds of signals are more persuasive, and (2) Information processing theories give answers to how and why customers rely on different online reviews in the decision process. Our study adds to the second stream of studies. Information processing theories highlight how the information receivers process the information (Li et al. 2017). For instance, according to Elaboration Likelihood Model (ELM), messages can be processed through two major routes: central route and peripheral route. The central route involves a high level of elaboration, while the peripheral route entails a low level of elaboration (Petty and Cacioppo 1986). Similar with ELM theory, Heuristic Systematic Model (HSM) argues that consumers apply two patterns (heuristic pattern and systematic pattern) when they deal with information. How to choose the pattern depends on efficiency and sufficiency of the patterns (Chaiken 1980; Chaiken and Maheswaran 1994).

Distinct from former studies analyzing from user-perspective, we turn to the signal-perspective when exploring how people process and evaluate information. We integrate IPM and MPAAM together to explain why customers rely on different reviews when they consult the online review sites with different information volume. Finally, we find that attractiveness, representation sufficiency, functional sufficiency are three key factors determining review helpfulness. And the effects are moderated by information volume. Figure 1 shows the research model of the present study.

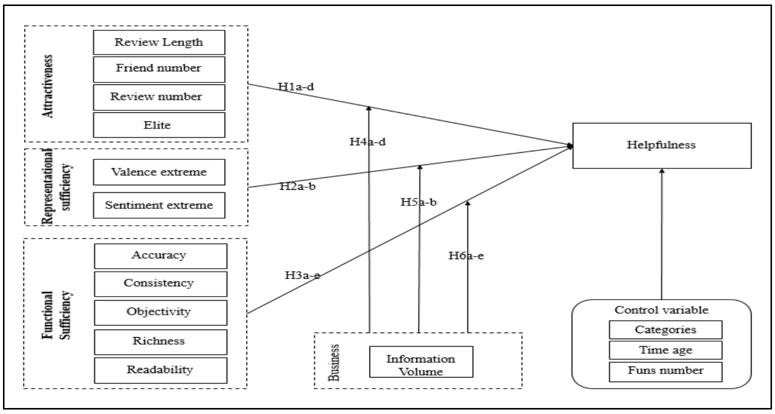

Figure 1. Research Model

Attractiveness: Review length, Review Number, Friend Number and Elite Label

IPM suggests there are three phases when people go through the information (Hovland and Weiss 1953; Howland et al. 1953). Beginning with message exposure, people go through message reception (attention and comprehension) and message yielding (evaluation, belief change, and attitude change). So when evaluating messages, people are influenced by both attention and comprehension. Figure 2 shows the information processing model. Current studies primarily looked into review helpfulness from diagnosticity-comprehension perspectives. However, with the increasing amount of information, not every review comes into customers' sights (Kuan et al. 2015). Considering the attractive nature, research found that vivid information has greater impact on choices relative to extensive but pallid information (Herr et al. 1991). Based on the notion that it seems less diagnostic for the information that is hard to retrieve, people may use the easiness of retrieving attitude to infer how important the attitude is (Bizer and Krosnick 2001; Roese and Olson 1994).

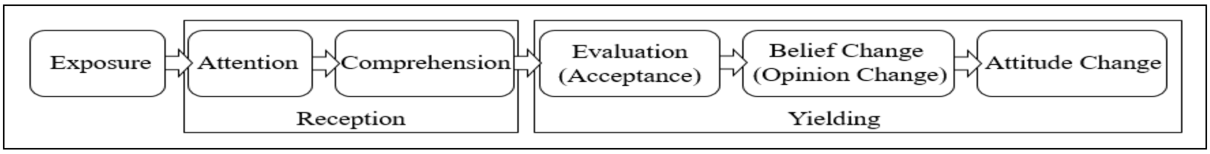

Figure 2. Information Processing Model (Hovland and Weiss 1953)

In the online review context, review length, review number, friend number and elite label are considered to indicate the attractiveness of the review. A longer review occupies larger space, which attracts more attention. In addition, it's common that long review containing heterogeneity information could be far more concrete and descriptive, which also makes it salient and less likely to be overlooked (Krishnamoorthy 2015). Hence, we hypothesize:

H1a: *A longer review is more likely to be rated as helpful.*

Besides the review itself, reviewer's characteristics also play important roles when analyzing review helpfulness. Review number of the reviewer, as symbol of experience and engagement, denotes the willingness and frequency of a reviewer in writing reviews. Prior studies found the positive association between reviewer's review number and trustworthiness (Zhou and Guo 2017); Similar to review number, an elite label (i.e., an elite reviewer has authority and is regarded as domain expert) is another indicator viewed as the credibility of the reviewer. Generally, elite reviewers have more capability to provide correct information. According to source credibility theory, besides expertise, sociability is another critical dimension influencing the source credibility. Related studies also found that the number of social ties correlate with trustworthiness (Prell 2003; Susarla et al. 2012). With lots of reviews on the website, reviews posted by reviewer with large review number, friend number or elite label are more attractive and less likely to be ignored. Thus, we hypothesize:

H1b: *A review from reviewer who has posted more reviews before is more likely to be rated as helpful.*

H1c: *A review from an elite is more likely to be rated as helpful.*

H1d: *A review from the reviewer who has more friends is more likely to be rated as helpful.*

Representational Sufficiency: Review Extremity

After attracting people's attention, people go through message yielding phase. Considering the purpose of consulting review websites is to help the web users build product attitude and make consumption decision. MPAAM model concerns how attitudes form and consequently guide the behavior (Cohen and AmericusReedII 2006). Beginning with an initial anchor attitude, people use representational sufficiency and functional sufficiency to denote the adequacy to use the retrieved or constructed attitude to guide behavior.

Representational sufficiency is an umbrella term referring to either the coherence of an attitude or the fluency with which it was retrieved (Lynch 2006). It is likely to be virtually an automatic reflection of whether what has been retrieved represents one's reasonably well-formed and coherent judgment as opposed to some hazy, vague thought with little sense of personal ownership (Lynch 2006). A representationally sufficient attitude feels authentic in some way, causing further information recruitment. Just as people may use the ease of retrieving an attitude to infer how important the attitude is, people may infer if the attitude is unambiguous and certain as well as confidently held. In the online review background, extreme review with one or five stars is much more representationally sufficient than neutral three-star review. Similarly, from the text analysis aspect, intense sentiment the content conveys (extremely positive or negative) is also more attractive as a kind of representational sufficiency.

H2a: *An extreme review with 1 or 5 stars is more likely to be rated as helpful.*

H2b: *An extreme review with intense sentiment is more likely to be rated as helpful.*

Functional Sufficiency: Accuracy, Consistency, Objectivity, Richness and Readability

Assuming that an attitude is representationally sufficient, but it still seems not adequate in guiding behavior. Even though representationally sufficient review conveys a clear and definite attitude, but whether the attitude is reliable is not assured. Functional sufficiency assessment, which we define operationally as a perceived readiness to engage in a behavior or to make a decision based on a retrieved attitude (Cohen and AmericusReedII 2006; Lynch 2006). It reflects the adequacy of the attitude for the judgment, choice, or action at hand. To be brief, it is needed to provide more detailed and persuasive evidences when people make decision relying on online reviews (Lynch 2006). In the current study, we are going from the aspects of review accuracy, consistency, richness, objectivity and readability to develop our hypotheses.

Review accuracy means the consistency between review valence and review content. Considering review valence (from 1 to 5 stars) and review content are two different systems, attitude the review content conveys may be different from the star rating. This inconsistency will confuse review readers and ultimately impair the review helpfulness. Based on cognitive dissonance theory, individuals strive to maintain a consistent set of beliefs and cognition inconsistency induces psychological tension (Hinojosa et al. 2017). So we believe accurate reviews are perceived more helpful.

H3a: *An accurate review is more likely to be rated as helpful.*

Researches show that a single review is often consulted together with the whole review set. Reviews which are consistent with the opinions of majority are easily adopt (Aghakhani et al. 2017). A common approach to judge whether the review is authentic is to compare the current review with other reviews and the consistent degree has a positive effect on the perceived eWOM credibility (Baek et al. 2012). These effects can be explained by the spreading activation model, which argues that things will go on smoothly when the current facts are consistent with prior knowledge and expectation. Eventually, the consistent review will be perceived more helpful.

H3b: *A consistent review is more likely to be rated as helpful.*

Objectivity is commonly distinguished from subjective, which emphasizes the sentences contain more factual details on product attributes. Conversely, subjective content contains more affective factors related to personal standards (Duhan et al. 1997). Prior studies found the extend of objectivity affects helpfulness by the extent of giving recipients more factual cues (Baek et al. 2012). On the contrary, subjective comments don’t reflect product characteristics precisely and should be attributed to reviewer’s personal reason. Thus, we hypothesize:

H4c: *An objective review is more likely to be rated as helpful.*

Information richness refers to the informativeness of the review (Park et al. 2007). Information richness emphasizes the number of information sets contained in the review content. It should be evaluated from the versatility and diversity aspects (i.e., reviews have more paragraphs). Limit product knowledge leads to customer’s decision uncertainty. The purpose of people searching on the review website is to gain product knowledge. So reviews that are rich in information have stronger effect on review helpfulness for the abundant product knowledge.

H3d: *A content-rich review is more likely to be rated as helpful.*

The readability is a kind of writing style which reveals the clarity of the expression. Readable review can effectively reduce the cognitive resources and help reader reach the core concepts quickly. Researches reveal that review is perceived more helpful if it is friendly to read (Korfiatis et al. 2012). Dividing long text into short sentences with little syllables and short words is an effective way to improve readability. In this paper, we use gunning fog index which is a readability test for English writing to measure readability.

H3e: *A readable review is more likely to be rated as helpful.*

Moderating Role of Information Volume

Customers use online reviews to make purchase decision. Under ideal conditions, consumers want to review all available information to have a comprehensive understanding toward the objects (Keller and Staelin 1987). In reality, the information environment is usually far from perfect. There are hundreds of reviews under every business in online review websites. It's impossible for people to distribute equal effort to every piece of review. Citing numerous laboratory experiment, findings show humans is cognitively limited and increasing information leads to poor decisions when they fail to deal with the well-intentioned information (Keller and Staelin 1987). From current studies, users might select a limited subset of the available reviews to read (Kwon et al. 2015). According to a survey, 67% of consumers reported that they feel they can trust a local business after reading 2 to 10 online reviews and ratings (25% said 2 to 3, 22% said 4 to 6, and 20% said 7 to 10). When enough information has been obtained, the rest reviews are left unconsidered. The competition among the reviews is getting fiercer with lots of reviews. Attractiveness becomes an even more critical factor and helps a review stand out from the crowd.

H4a-d: *The positive effects of the review length (H4a), post number of the reviewer (H4b), elite (H4c), friend number of the reviewer (H4d) on helpfulness are positively moderated by information volume.*

Based on attribute theory, extreme reviews are easily attributed to internal motivation related to personal reasons. Even though a clear-cut review with definite attitude directly gives the advice and saves the efforts used for extracting viewpoints, people will simultaneously suspect why the reviewer is so extreme. The reliability of extreme and curt reviews will be challenged for the lack of sufficient evidences. With the increasing information quantity, people will be more cautious. Functional sufficiency just satisfies our need of learning about the realistic basis for doing so. When review set is large, functional sufficiency related factors ensure the review's credibility to some degree. From this aspect, information volume moderates the effect of representational sufficiency and functional sufficiency on helpfulness.

H5a-b: *The positive effect of review valence extreme (H5a) and review sentiment extreme (H5b) on helpfulness is negatively moderated by information volume.*

H6a-e: *The positive effect of the review accuracy (H6a), consistency (H6b), objective (H6c), richness (H6d), and readability (H6e) on helpfulness is positively moderated by information volume.*

Methodology

To validate the research model, we randomly collected a total of 40985 reviews in Yelp.com during the Yelp Dataset Challenge Round 9 in June 2017 (https://www.yelp.com/dataset_challenge).

Measurements

Unlike previous studies which generally apply direct data from the website, we innovatively use the natural language processing tools called TextBlob to calculate sentiment value and objectivity of the text content of the review. Table 1 shows the measurements of the variables for empirical analysis.

Table 1. Variable Table

Variables		Measurements
Review Usefulness (DV)	Useful Vote	Number of useful votes the review gained.
Attractiveness (IV)	Text Length	Word number of the review.
	Friends Number	Friend number of the reviewer.
	Review Number	Total review number post by the reviewer.
	Elite	"Elite" refers to if the reviewer is an elite user, which is operationalized as a binary variable, the elite member is assigned as "1"; otherwise, as "0".

Representational Sufficiency (IV）	Valence Extreme	“Valence extreme” refers to the extreme level of voting star. We view 3 stars is neutrality, so we take the absolute value of the voting star minus 3 stars as the review’s valance extreme.
	Sentiment Extreme	The sentiment value calculated through TextBlob is from -1 to 1. We use the absolute value of the sentiment value of the review content to represent “sentiment extreme”.
Functional Sufficiency (IV)	Consistency	The distance between the voting star to average star.
	Accuracy	We measure “accuracy” by the distance between review voting star and sentiment value after standardization.
	Objectivity	Subjectivity is from the sentiment analyzing of the review content, which is range from -1 to 1.
	Richness	Number of paragraphs of the review content.
	Readability	Gunning fog index= 0.4[(words/sentences) +100(complex words/words)].
Information Volume (MV)	Information Volume	Total number of reviews received by the business.
Others (Control Variables)	Funs Number	Funs number of the reviewer.
	Categories	Nightlife/ restaurant/ home service/ others (1/2/3/4).
	Time Age	Days from the review was post until now.

Descriptive statistics

Table 2 presents a summary of descriptive statistics for all the variables in the sample.

Table 2. Descriptive Statistics

Variables	Mean	Std. Dev.	Min	Max	VIF	1/VIF
useful	0.99	2.38	0	207	Mean VIF=1.89	
elite	0.29	0.45	0	1	1.88	0.53
friends_num	109.28	350.96	0	5791	3.73	0.27
post_num	127.46	240.23	0	2061	3.22	0.31
logreview_~s	6.12	0.82	2.64	8.52	1.96	0.51
valence_ex~m	1.41	0.71	0	2	1.65	0.61
sentiment_~m	0.27	0.18	0	1	1.7	0.59
consistency	1.46	2.10	0	16	1.68	0.59
accuracy	0.26	1.19	-4	4	1.63	0.61
richness	2.59	4.32	0	70	1.62	0.62
subjectivity	0.55	0.14	0	1	1.33	0.75
readability	8.91	3.95	0	155	1.1	0.91
logbusines~t	4.57	1.61	1.39	8.77	1.13	0.88
logday	6.97	0.63	5.63	8.34	1.11	0.90
categorites	1.99	1.28	1	4	1.16	0.86
funs	9.80	34.76	0	1330	3.49	0.29

Preliminary Results

We adopt the negative binomial model because it can correct over-dispersion and account for the omitted variable bias in this paper. Table 3 shows the preliminary results, which suggests interesting findings regarding the relationships in the research model (e.g., the differential effects of review characteristics on review helpfulness and the moderating effects of information volume). Next, we will further explore these relationships by using more complex techniques such as the seemingly unrelated regression (SUR) Tobit model and order Probit model.

Table 3. Negative Binomial Model Results

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
logday	0.3257***	0.2473***	0.2131***	0.2101***	0.2087***
categorites	0.0902***	0.0699***	0.0689***	0.0710***	0.0723***
funs	0.0161***	0.0058***	0.0058***	0.0060***	0.0060***
logreview_words		0.4318***	0.3689***	0.3512***	0.3473***
post_num		-0.0004***	-0.0009***	-0.0009***	-0.0009***
elite		0.6578***	0.6807***	0.5864***	0.5223***
friends_num		0.00046***	0.0008***	0.0007***	0.0007***
valence_extrem		0.3060***	0.3253***	0.2361***	0.2333***
sentiment_extrem		-0.4529***	-0.4370***	-0.8636***	-0.7022***
accuracy		-0.1442***	-0.1537***	-0.1518***	-0.2391***
consistency		0.0012	0.0022	0.0014	-0.0038
subjectivity		0.0204	0.0133	0.0178	0.3686*
richness		0.0312***	0.0283***	0.0286***	0.0359***
readability		-0.0099***	-0.0087**	-0.0087**	-0.0208**
logbusiness_review_count			-0.1732***	-0.2041***	-0.1407**
logbusi_re_words			0.0116	0.0145*	0.0142**
logbusi_re_post			0.0305***	0.0251***	0.0206***
logbusi_re_elite			-0.0531***	-0.0349***	-0.0233
logbusi_re_friends			-0.0001**	-0.00005**	-0.00004*
logbusi_re_sentiment				0.1166***	0.0798**
logbusi_re_extrem				0.0187*	0.0160
logbusi_re_accuracy					0.0251***
logbusi_re_consistency					0.0012
logbusi_re_subjective					-0.0835*
logbusi_re_richness					-0.0017
logbusi_re_readability					0.0035*
_cons	-2.7766***	-5.3806***	-4.7022***	-4.4136***	-4.5582***
Wald chi2(d.f.)	2022.5900	10174.6500	10501.7300	10469.2400	10645.8400
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000
Log pseudolikelihood	-52638.1020	-49425.0420	-49282.1600	-49267.8940	-49239.0940
Pseudo R^2	0.0501	0.1055	0.1080	0.1083	0.1088

Note: The dependent variable is useful vote.

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