Technological and Economic Development of Economy
ISSN: 2029-4913 / eISSN: 2029-4921
2018 Volume 24 Issue 5: 2045–2064
https://doi.org/10.3846/tede.2018.4545

THE DYNAMIC EFFECTS OF ONLINE PRODUCT REVIEWS ON PURCHASE DECISIONS

Jia CHEN[1], Gang KOU[2], Yi PENG[1]*

[1]*School of Economics and Management, University of Electronic Science and Technology of China, Chengdu, 611731, China*
[2]*School of Business Administration, Southwest University of Finance and Economics of China, Chengdu, 610074, China*

Received 31 July 2017; accepted 24 March 2018

Abstract. Previous studies have demonstrated that online reviews play an important role in the purchase decision process. Though the effects of positive and negative reviews to consumers' purchase decisions have been analyzed, they were examined statically and separately. In reality, online review community allows everyone to express and receive opinions and individuals can reexamine their opinions after receiving messages from others. The goal of this paper is to study how potential customers form their opinions dynamically under the effects of both positive and negative reviews using a numerical simulation. The results show that consumers with different membership levels have different information sensitivities to online reviews. Consumers at low and medium membership levels are often persuaded by online reviews, regardless of their initial opinion about a product. On the other hand, online reviews have less effect on consumers at higher membership levels, who often make purchase decisions based on their initial impressions of a product.

Keywords: opinion evaluation, online reviews, membership level, purchase decision.

JEL Classification: C80.

Introduction

The impact of online product reviews on e-commerce can be significant since potential online customers often refer to online reviews from previous customers before making their purchase decisions (Banerjee, Bhattacharyya, & Bose, 2017; Liu, 2006). A survey showed that 90% consumers read online reviews and 83% of them agree that online reviews affect their final decisions (Channel Advisor, 2011).

Previous studies of the influence of online reviews on e-commerce focus on two aspects: market-level and individual-level (J. Lee & J. N. Lee, 2009; Ye & Li, 2017). Individual-level analysis emphasizes key variables (such as product attitude (Wang, Teo, & Wei, 2015; Kou,

*Corresponding author. E-mail: *pengyi@uestc.edu.cn*

Lu, Peng, & Shi, 2012; Lee, Park, & Han, 2008), product intention (J. Lee & J. N. Lee, 2009), adoption of online reviews (Cheung, Luo, Sia, & Chen, 2009; Park & Kim, 2008; Park & Lee, 2008) and has attracted growing attention (Zhang, Zhao, Cheung, & Lee, 2014). Among these studies, dual-process theories (i.e., elaboration likelihood model (ELM) and heuristic-systematic model (HSM)) discuss how individuals establish assessments and make decisions during information processing (Eagly & Chaiken, 1993; Cheung & Thadani, 2012; Zhang et al., 2014; Kou, Peng, & Wang, 2014a). The dual-process theories show that individuals consider all relevant information before forming a judgment and making a decision (Zhang et al., 2014; Ye & Li, 2017).

However, ELM and HSM models have some limitations. First, the two models emphasize the persuasion outcomes of online reviews on individuals, which are static information process. It is unclear how individual handles each piece of information during the decision making process. In fact, when consumers encounter the opinions of other consumers for a product they wish to purchase, their own initial opinions gradually changes dynamically (Park & Kim, 2008; Wu & Kou, 2016). Therefore, it is meaningful to study how do consumers form their opinions dynamically under the influence of online product reviews. The second limitation of the dual-process models is that they analyze the effects of positive and negative online reviews separately. In reality, individuals read both positive and negative comments simultaneously (Park & Kim, 2008; Kou & Lin, 2014b). It is interesting to analyze how individuals make purchase decisions with mixed online reviews.

The goal of this paper is to study the dynamic information process of consumers and analyze what is an individual's final attitude when affected by both positive and negative comments. This study revised the Receipt-accept-sample (RAS) model, which was developed to analyze the attitude change of voters (Zaller 2005), to examine individual' attitude change under the influence of online product reviews. Through the experiment, we simulated different opinions of online reviews and individuals' information processes. The findings of this study help us better understand online consumers' behaviors and can be useful for designers of e-commerce web sites and marketers.

The rest of this paper is organized as follows. Section 1 reviews the literature of dual-process theory, process of opinion evaluation, and the RAS model. Section 2 presents the proposed opinion evaluation methodology and model. Section 3 describes the computer simulation used to analyze consumer opinion evaluation and discusses the results. The final section concludes the paper.

1. Literature review

This study analyzes how online reviews affect potential consumers' purchase decision dynamically from the perspective of opinion evaluation. This section introduces the dual-process theory, process of opinion evaluation in contemporary social psychologists, and the receipt-accept-sample (RAS) model of opinion evaluation.

1.1. Dual-process theory

Electronic word of mouth (eWOM) increases the power of peer-to-peer communication among individuals (Wu, 2017; Dellarocas, Zhang, & Awad, 2007; Eldomiaty, Rashwan, Din &

Tayel, 2016). The ELM and HSM are the theoretical foundations in studying the impact of eWOM communication (Cheung & Thadani, 2012). Previous studies employ the ELM and HSM models to analyze the effects of online reviews on consumers' purchase decisions from two aspects (Zhang et al., 2014; Park, Lee, & Han, 2007; Chan & Ma, 2016):

1) What factors make important effects during the information processing? Identified factors of eWOM include quantity (Park et al., 2007), quality (Cheung & Lee, 2012; Park et al., 2007), credibility (Zhang et al., 2014; Wu, Wang, Ma & Ye, 2017), and the type of reviews (Floyd, Freling, Alhoqail, Cho, & Freling, 2014; Cheung & Thadani, 2012; Park & Kim, 2008). These factors are divided into central route and peripheral route to analyze the effect of eWOM on consumers' persuasion. The central route means that individuals with high elaboration tend to think about information carefully. This is a process of consumers consciously changing their attitudes. Individuals are usually quite rational and make a systematic use of available information (Ajzen & Fishbein, 1980). The peripheral route means that individuals with low elaboration tend to evaluate information with minimum effort (Lee et al., 2008). This is a **spontaneous** processing of consumers changing their attitudes. In this process, individuals' attitude is largely a function of perception in the immediate situation (Kou, Ergu, & Shang, 2014c; Fazio, 1990). When consumers make purchase decisions using online reviews, their attitudes are often influenced by the perceived comments of online reviews. Therefore, consumers' attitudes are spontaneous process of change (Kou, Ergu, Lin, & Chen, 2016). At the same time, consumers process online reviews one at a time and form their opinions about products gradually. It is interesting to study how do consumers process each online review and reach their final decision dynamically.
2) How do these factors affect an individual's information process? Prior studies shows that quantity and quality of eWOM are positively related to the purchase intentions (Cheung & Thadani, 2012; Park et al., 2007; Xia & Hou, 2016) and eWOM credibility is positively related to the purchase decisions (Cheung & Thadani, 2012; Cheung et al., 2009). Online reviews are typically presented in three forms: positive, neutral, or negative reviews. Most consumers assume that a neutral review often reflects a negative view (Pang & Lee, 2008). Therefore, this paper considers neutral feedback as a negative review. Positive reviews often have positive effects on individuals' attitudes toward products (Floyd et al., 2014; Mukhopadhyay, 2016). In contrast, negative reviews usually negatively affect individual perception of products (C. Luo, X. Luo, Xu, Warkentin, & Sia, 2015; Cheng & Ho, 2015; Floyd et al., 2014; Berger, Sorensen, & Rasmussen, 2010). Though the effects of positive and negative reviews independently on individuals' decision-making processes have been analyzed, no study, to the best of our knowledge, has considered the effects of positive and negative reviews simultaneously on consumer decisions.

1.2. Process of opinion evaluation and attitude change

Attitude change usually starts from eWOM persuasion (Filieri, 2015) and is a part of the information processing. Processing information directly or indirectly affects individual attitudes (Petty & Cacioppo, 1984). In general, attitude change requires a 12-step sequence: exposure, attention, interest, comprehension, acquisition, yielding, memory, retrieval, decision, action, reinforcement, and consolidation (Petty & Cacioppo, 1984; Figure 1). Studies often describe the persuasion process using several steps from the whole process, while excluding other steps (Petty, Tormala, Briüol, & Jarvis, 2006).

The persuasion process often occurs when an individual is exposed to some new information, which may or may not attract an individual's attention. If the individual pays attention to the information and finds it interesting, the next two stages of comprehension and acquisition ensure that the individual learns and understands the information. The change of attitude mostly occurs in the yielding stage. General information processing suggests that a change early in the sequence would inevitably lead to a change later in the sequence (Petty et al., 2006). Over time individuals often develop their personal knowledge about the tactics used in persuasion process. This knowledge called persuasion knowledge, usually helps individuals adaptively respond to persuasion attempts and achieve their own goals (Friestad & Wright, 1994). The development of persuasion knowledge depends on some basic cognitive skills and individuals accumulated experience in social encounters. Simultaneously, persuasion knowledge development can increase individuals' information processing capabilities (Deborah, John, & Whitney, 1986; Tee & Ong, 2016).

This study uses this theory to discuss the effect of online review valence (positive review and negative review) on individual opinion evaluation and attitude formation toward a product.

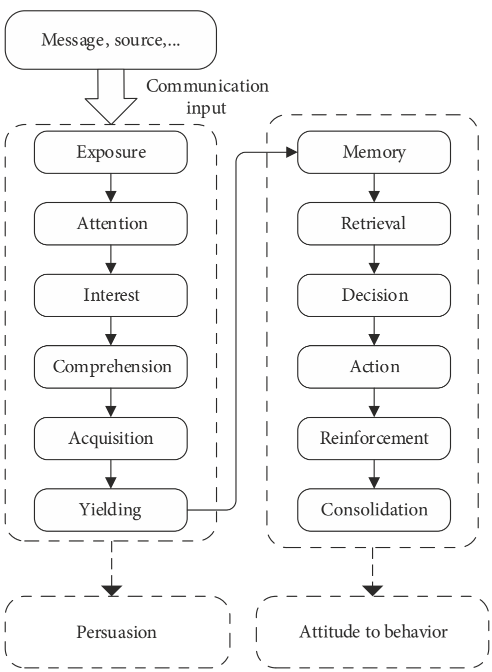

Figure 1. Process of persuasion and attitude change (Petty & Cacioppo, 1984)

1.3. Receipt-accept-sample (RAS) model

When presidential candidates are running for election, they utilize a variety of campaigns. Zaller (2005) analyzes the attitude change of voters under RAS model during an election. He found that when people receive various messages regarding a candidate and often have three reactions: either in favor of, opposed to, or neglecting. These reactions can be interpreted as receiving and accepting the information, receiving but not accepting the message, and neglecting the message (Deng, Liu, & Zeng, 2012).

In Zaller (2005), When an individual agrees with the presented opinion, the reception probability of an individual is defined as follows:

$$P_r(m_0,\ m_1,\ W_i) = 1 - \frac{1}{1 + f + e^{\left(m_0 + m_1 * W_i\right)}}, \tag{1}$$

where f represents the floor level of reception; in most cases, f equals 0. m_0 denotes the intensity of the given message, and m_1 denotes the strength of the relationship between the individual's awareness and the reception probability of the message. W_i describes the individual's awareness level, which is often affected by his/her own knowledge and experience of the information. With more knowledge of the information, the individual usually has a higher degree of awareness.

When receiving information, the probability of an individual accepting it is defined as:

$$P_a(W_i, L_i; n_0,\ n_1,\ n_2) = \frac{1}{1 + e^{\left(-n_0 - n_1 * W_i - n_2 * L_i\right)}}, \tag{2}$$

where n_0 is the credibility of the given message, n_1 is the resistance of the individual's awareness to persuasion of the given message, and n_2 is the resistance of the individual's predisposition to persuasion. L_i is the individual's predisposition to accept the given information, which defines the distance of predisposition and acceptation of information. W_i retains the same meaning.

When an individual receives a message and then accepts the opinion, the probability is as follows:

$$P_s = P_r(m_0,\ m_1,\ W_i) * P_a(W_i, L_i; n_0,\ n_1,\ n_2). \tag{3}$$

Receiving and accepting information means that individual is persuaded by the message. The Zaller model describes the process of receipt message by individuals of accepting the message or not and captures individuals-level differences in both reception of and persuasive information. Meanwhile, it accommodates opinion change over time periods (Kulakowski, 2009).

Thus, researchers consistently discuss opinion evolution based on RAS model. For example, using a free parameter, presented correlations between previously and newly received messages, Kulakowski (2009) argues that individuals' political awareness increase with time first exponentially, later linearly. Then, Deng et al. (2012) investigate the process of opinion evolution, based on different factors of public opinion. The method gives a connection between macroscopic dynamics and microscopic behavior.

This paper proposes an integrated model of opinion evaluation based on the RAS model to investigate the process of individuals receiving and re-examining their opinions. Using the integrated model, we can know more the dynamic impact of online reviews on consumer decision-making.

2. Integrated model of opinion evaluation

Though RAS model describes individual' information process, it does not analyze how individuals handle positive and negative online reviews. This study redefines the rules of individual's opinion evaluation underling positive and negative reviews based on RAS model. Through the integrated model, we can better understand the effect of online reviews on individual' purchase decision in dynamic information process.

Online forums provide numerous communication opportunities to consumers (Kim, Jang, & Adler, 2015) and allow everyone to express their views and receive opinions from others (Libai et al., 2010). As a result, individuals often re-examine his/her opinions after receiving messages from others (Deng et al., 2012). Before consumers make a purchase decision, they often pay attention to online reviews and have three basic reactions to online messages (Deng et al., 2012):

1) Receive and accept the opinion of a message.
2) Receive a message, but do not accept the opinion.
3) Ignore a message, indicating a neutral opinion of the message.

When consumers refer to an online community before making a purchase decision, they often encounter positive, neutral, and negative reviews. Since most consumers assume that neutral reviews reflect a negative view (Pang & Lee, 2008), this study treats neutral reviews as negative. Therefore, we can describe consumers' reactions using one of the following categories (Figure 2):

1) Individuals will re-evaluate opinions to strengthen their initial opinions assuming receiving and accepting supporting information (the opinion of information is consistent with initial information) in time *t*, although they initially retain a positive (negative) or no opinion.
2) Assume individual accepts an opposing information, having received it, and cannot accept supporting information (whether received or not) in time *t*, they will re-evaluate their initial opinions to support the opposing opinion (the opinion of information is inconsistent with initial information.), despite holding a positive (negative) or no opinion initially.
3) Individuals will re-evaluate toward no opinion (neutral) assuming that they ignore all incoming information (positive or negative messages), or accept both positive and negative information in time *t*.

Based on the equations (1) and (2) in the RAS model, we define consumers' reactions dynamically as follows:

1) If an individual *i* receives a positive review in period *t*, the probability is defined as follows:

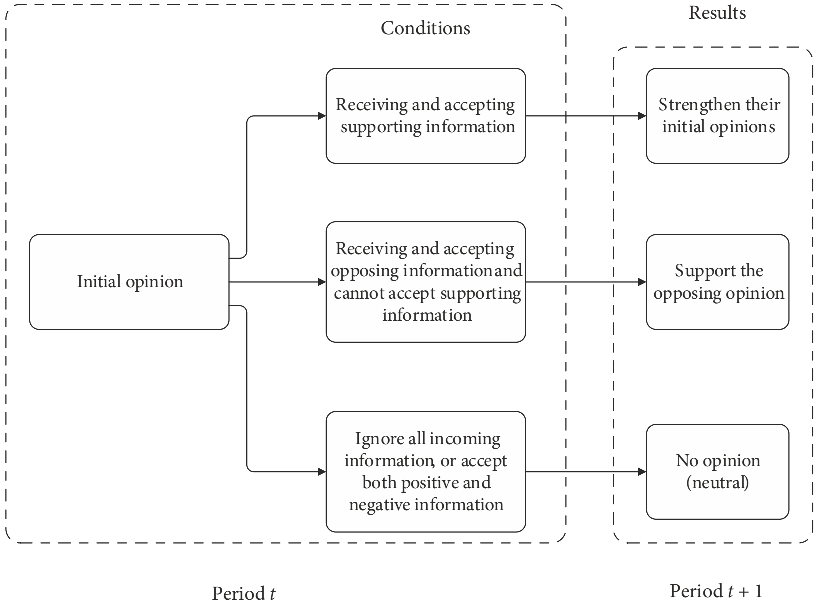

Figure 2. Three consumer reactions to online reviews

$$P_{rpt}(m_{0pt},\ m_1,\ W_i) = 1 - \frac{1}{1 + f + e^{\left(m_{0pt} + m_1 {}^* W_i\right)}} = R_{ipt}, \tag{4}$$

where m_{0tp} is the intensity of the incoming positive review in period t, and f, m_1, W_i have the same meaning as in Eq. (1).

2) If an individual i accepts a positive review in period t, the probability is defined as

$$P_{apt}(W_i, L_i; n_{0pt},\ n_{1t},\ n_{2t}) = \frac{1}{1 + e^{\left(-n_{0pt} - n_{1t} {}^* W_i - n_{2t} {}^* L_i\right)}} = A_{ipt}. \tag{5}$$

where n_{0tp} is the credibility of the incoming positive review in period t, n_{1t} is the resistance of the individual's awareness to persuasion of the message in period t, and n_{2t} is the resistance of the individual's predisposition to persuasion in period t. L_i has the same meaning as in Eq. (2).

In period t, if the individual receives a negative review, it is defined as R_{int} and accepts a negative review is A_{int}.

If the individual ignores all incoming information (positive or negative), or accepts both positive and negative information in time t, the individual will decay toward having no opinion in a fixed probability d (Zaller, 2005).

Thus, assuming a positive opinion in period t, the probability of holding a negative opinion in period $t + 1$ is:

$$P_{\gg Nt+1} = \left[R_{int} {}^* (1 - R_{ipt}) \right]^* A_{int} + R_{ipt} {}^* R_{int} \left[A_{int} \left(1 - A_{ipt}\right) \right]. \tag{6}$$

Assuming a negative opinion in period t, the probability of transforming to a positive opinion in period $t + 1$ is:

$$P_{\gg Pt+1} = \left[R_{ipt} * (1 - R_{int}) \right] * A_{ipt} + R_{ipt} * R_{int} \left[A_{ipt} \left(1 - A_{int} \right) \right]. \tag{7}$$

Suppose an individual has an opinion in time t, the probability that the individual changes to have no opinion in period $t + 1$ is:

$$P_{\gg No\,t+1} = d * \left[1 - P_{\gg Pt+1} - P_{\gg Nt+1} \right]. \tag{8}$$

The probability of opinion evaluation is a simple Markov system. Considering any past time (…, t–2, t–1), assuming the value of $X(t)$ denotes an individual's state in time t, an individual' state in time $t + 1$ is:

$$P\left[X(t+1) = x(t+1) \mid X(t) = x(t), X(t-1) = x(t-1), \ldots) \right] =$$
$$P\left[X(t+1) = x(t+1) \mid X(t) = x(t) \right]. \tag{9}$$

Under the Markov system, if $P_{\gg Nt+1}$ is larger than $P_{\gg Pt+1}$ and $P_{\gg No\,t+1}$, individual i will change his/her opinion to negative in state $X(t+1)$. Assuming $P_{\gg Pt+1}$ is larger than $P_{\gg Nt+1}$ and $P_{\gg No\,t+1}$, individuals will evaluate their opinion with positive information. Otherwise, if $P_{\gg No\,t+1}$ is larger than $P_{\gg Nt+1}$ and $P_{\gg Pt+1}$, individuals will hold no opinion with incoming information.

Therefore, assuming that an individual's opinion is $X(t)$ in period t, the opinion in $X(t+1)$ is defined as follows:

$$X(t+1) = Max\left\{ P_{\gg Pt+1}, P_{\gg Nt+1}, P_{\gg No\,t+1} \right\}. \tag{10}$$

3. Numerical simulation and discussion

When individuals receive opinions and re-examine their own, the dynamics of opinion interactions cannot be directly measured in observational outcomes (Muchnik, Aral, & Taylor, 2013). Therefore, this study uses simulation to describe the dynamic information process. We designed an experiment to analyze the opinion evaluation process of individuals under the influence of online reviews. Section 3.1 gives research design, 3.2 describes the parameter settings in the simulation, and 3.3 analyzes the results.

3.1. Research design

Positive and negative online product reviews are usually random. The simulation assumes that online review opinions are random values and range from –2 to 2. A value of 2 means the highest positive review of a product and –2 indicates the most negative review (Deng et al., 2012). Initial opinions of individuals were 0.5, 0, or –0.8, which indicate a positive opinion, no opinion, or negative opinion about a product at the beginning (Deng et al., 2012).

To study the dynamic process of consumers' opinion evaluation, we set the number of messages from 0 to 2000, and their values were randomly distributed between –2 and 2. The simulation was conducted using Mat Lab 8.0 (Matlab, 2013) on computer of i5-4200H (4CPU, 2GHz), 4GB RAM.

3.2. Parameter assignment

Membership is defined as individuals' identification in a community (Hsu & Liao, 2014). Prior study shows that membership is the key determinant of virtual community' cohesion (Luo et al., 2015). Membership levels at online shopping sites describe the degree of engagements and the amount of money of online shopping consumers. It also reflects consumers own involvement and expertise experience (persuasion knowledge), which significantly affect how eWOM information is processed (Luo et al., 2015). Previous study indicates individuals' characteristics (e.g., persuasion knowledge) significantly affect their evaluation criteria for the received eWOM information (Luo et al., 2015). Individuals with high membership levels may evaluate information using different criteria, compared with other low membership level individuals (Ridings, Gefen, & Arinze, 2002).

Prior study shows that a higher membership level means more awareness of products and platforms (Fu & Wang, 2013). For instance, 360BUY.com, a large integrated network of retailers, divides membership levels into 10 groups and each level ranges from 0 to 10 (Fu & Wang, 2013). Thus, in Eq. (1) and (2), this study assumes that the awareness is linearly related to membership levels, namely, $W_i = k_1 \times R_i$, R_i is the membership level and k_1 is the correlation coefficient. We assume that membership levels are numerical values and R_i ranges from 0 to 10. At the same time, we assumed that the R_i is generally related to W_i, and set $k_1 = 0.3$, $R_i \in (0,10)$.

More often than not, individuals cannot read every online review. Rather, they read only part of the reviews that they consider important. A prior study found that the ratio of positive reviews has positive effect on the product sales (Babic, Sotgiu, De Valck, & Bijmolt, 2016). Thus, this study redefines information intensity as the ratio of positive reviews over online reviews in Eq. (1):

$$\text{Intensity} = \frac{\sum_{i=1}^{M} \text{positive reviews}}{\sum_{j=1}^{N} \text{online reviews}} \quad (i = 1, 2, 3 \ldots j = 1, 2, 3 \ldots). \tag{11}$$

where M is the total number of positive reviews, N is the total number of online reviews of the product.

For example, Philips Shaver has 107267 reviews on 360BUY.com, a large network of retailers (Fu & Wang, 2013). Among the reviews, 103391 are positive and 3876 are negative. The positive intensity of this product is 0.96 and the negative intensity is 0.04. We also calculate the intensity of other intended products with this equation. The simulation assumes that the information intensity of positive reviews is 0.96 and that of negative intensity is 0.04 (Deng & Liu, 2011).

In Eq. (1), m_1 is the relationship between awareness and reception, which is distinct for each individual. In many cases, individuals tend to "suddenly realize" having a certain awareness (Kulakowski, 2009). We assume the value of m_1 as a truncated exponential function from [0, 2] (Deng et al., 2012).

Many researchers are interested in the credibility of online review valence. Most studies find that negative reviews are more important than positive ones in consumers purchase decisions (Ullah, Amblee, Kim, & Lee, 2016; Pietri & Shook, 2013; Lee & Koo, 2012; Lee et al., 2008). Therefore, we assume the information credibility of negative and positive reviews as 0.6 and 0.4, respectively.

In Eq. (2), n_1 measures the effect of awareness on resistance to persuasion by an incoming message (Deng et al., 2012). As we cannot foresee an individual's situation, we assume that n_1 follows a random even distribution in [–2, 0] (Deng et al., 2012).

In Eq. (2), n_2 is the stubbornness level of an individual. Existing research discovered that higher the level of stubbornness, the more persistent an individual's views are (Deng et al., 2012; Khare, Labrecque, & Asare, 2011). Thus, we assume that individual stubbornness levels follow a normal distribution from [0, 5].

In Eq. (2), L_i measures the distance between an individual's opinion and an incoming message. The value of L_i is usually coded from –1 to 1 (Deng et al., 2012). –1 indicates a huge difference between two opinions and 1 describes a perfect consistency between two opinions.

Table 1. The change of RAS model to integrated opinion evaluation

RAS model	Condition of model	Integrated model of opinion evaluation
The reception probability is: $P_r(m_0,\ m_1,\ W_i) = 1-\frac{1}{1+f+e^{(m_0+m_1*W_i)}}$. The accepting probability is: $P_a(W_i,L_i;n_0,\ n_1,\ n_2) = \frac{1}{1+e^{(-n_0-n_1*W_i-n_2*L_i)}}$. Individual receives a message and then accepts the opinion, the probability is as follows: $P_s = P_r(m_0,\ m_1,\ W_i)* P_a(W_i,L_i;n_0,\ n_1,\ n_2)$.	1) Self-awareness is linearly related to the membership levels: $W_i = k_1 \times R_i$. 2) The definition of message intensity is as follows: $m_0 = \frac{\sum_{i=1}^{M}\text{positive reviews}}{\sum_{j=1}^{N}\text{online reviews}}$. 3) If $X_i(t) - X_j(t)\vert \le 0.5$, then $L_i = 1$,otherwise, $L_i = -1$.	If an individual i receives a positive review in period t, the probability is defined as follows: $P_{rpt}(m_{0pt},\ m_1,\ W_i) = 1-\frac{1}{1+f+e^{(m_{0pt}+m_1*W_i)}} = R_{ipt}$. If an individual i accepts a positive review in period t, the probability is defined as $P_{apt}(W_i,L_i;n_{0pt},\ n_{1t},\ n_{2t}) = \frac{1}{1+e^{(-n_{0pt}-n_{1t}*W_i-n_{2t}*L_i)}} = A_{ipt}$. If the individual receives a negative review, it is defined as R_{int} and accepts a negative review is A_{int}. Then the probability of holding a negative opinion in period $t + 1$ is: $P_{\gg Nt+1} = \left[R_{int} * (1-R_{ipt})\right]*A_{int} + R_{ipt} * R_{int}\left[A_{int}\left(1-A_{ipt}\right)\right]$. The probability of transforming to a positive opinion in period $t + 1$ is: $P_{\gg Pt+1} = \left[R_{ipt} * (1-R_{int})\right]*A_{ipt} + R_{ipt} * R_{int}\left[A_{ipt}\left(1-A_{int}\right)\right]$. The probability that the individual changes to have no opinion in period $t + 1$is: $P_{\gg Not+1} = d*\left[1-P_{\gg Pt+1}-P_{\gg Nt+1}\right]$. The opinion in $X\left(t+1\right)$ is: $X\left(t+1\right) = Max\left\{P_{\gg Pt+1}, P_{\gg Nt+1}, P_{\gg Not+1}\right\}$.

We introduce the Deffuant model to measure two opinions (Deffuant, Neau, Amblard, & Weisbuc, 2000). In this model, for n ($n \geq 2$) individuals of group, individual i holds an opinion $X_i(t)$ in time t, who will change their opinion to individual j's $X_j(t)$ in period $t + 1$ if the following holds true:

$$|X_i(t) - X_j(t)| \leq \varepsilon \; (\varepsilon \in (0,1)). \tag{12}$$

The opinion of individual i in period $t + 1$ will change to:

$$X_i(t + 1) = X_i(t) + \varphi[X_j(t) - X_i(t)] \; (\varphi \in (0, 0.5)). \tag{13}$$

Using the Deffuant model, we assume $\varepsilon = 0.5$, and $\varphi = 0.4$. Therefore, if $|X_i(t) - X_j(t)| \leq 0.5$, then $L_i = 1$; otherwise, $L_i = -1$.

In addition, we assume the value for the fixed probability d is 0.2 in Eq. (8).

For a better understanding, the change in the RAS model is summarized in Table 1.

3.3. Simulation results

To investigate consumer's opinion evaluation with continuous messages, we set the number of messages from 0 to 2000 to represent the whole process. In Figure 3, the x-axis represents the time steps, every time step represents a randomly message. The y-axis is the opinion value, which ranges from –2 to 2. Figures on the left show time steps from 0 to 100, and the figures on the right show time steps range from 0 to 2000. The initial opinions of individual are 0.5, 0, and –0.8, respectively, in Figure 3 a), b), and c).

In Figure 3, with a lower membership level ($R_i = 1$), individual's opinion fluctuates substantially, regardless of their initial opinions. In 100 time messages, individuals examine their opinions with every incoming message and without a stable opinion. When the number of messages increased to 2000, we see that an individual's opinion fluctuates with incoming online reviews. This indicates that individuals with low membership levels are easily persuaded by incoming online reviews, regardless of the number of online reviews. With low membership level, individuals' involvement and expertise experience are not rich, while persuasion knowledge is not enough. Therefore, they are always in adaption opinion of others to establish own judgments.

In Figure 4, the initial opinions of individual are 0.5, 0, and –0.8, respectively, in a), b), and c). Opinions of individuals with medium membership levels ($R_i = 5$) become stable after reading sufficient online reviews. In 100 time messages scenario, individuals always keep their previous opinions for a period time. However, they will examine their opinions if they accept a new message, whether it is positive or negative. In 2000 time messages, individuals examine their opinions in a stable situation with a great number of messages. Interestingly, the stable state of an individual's opinion can be negative or positive, regardless of whether their initial opinion was positive or negative. If individual only accept positive opinion of messages in a certain period time before the stable state, and then the individual will evaluate a positive opinion in the stable state, otherwise for the negative opinion stable state. However, once individuals are in a stable situation and have an extreme opinion of a product, online reviews will not affect them.

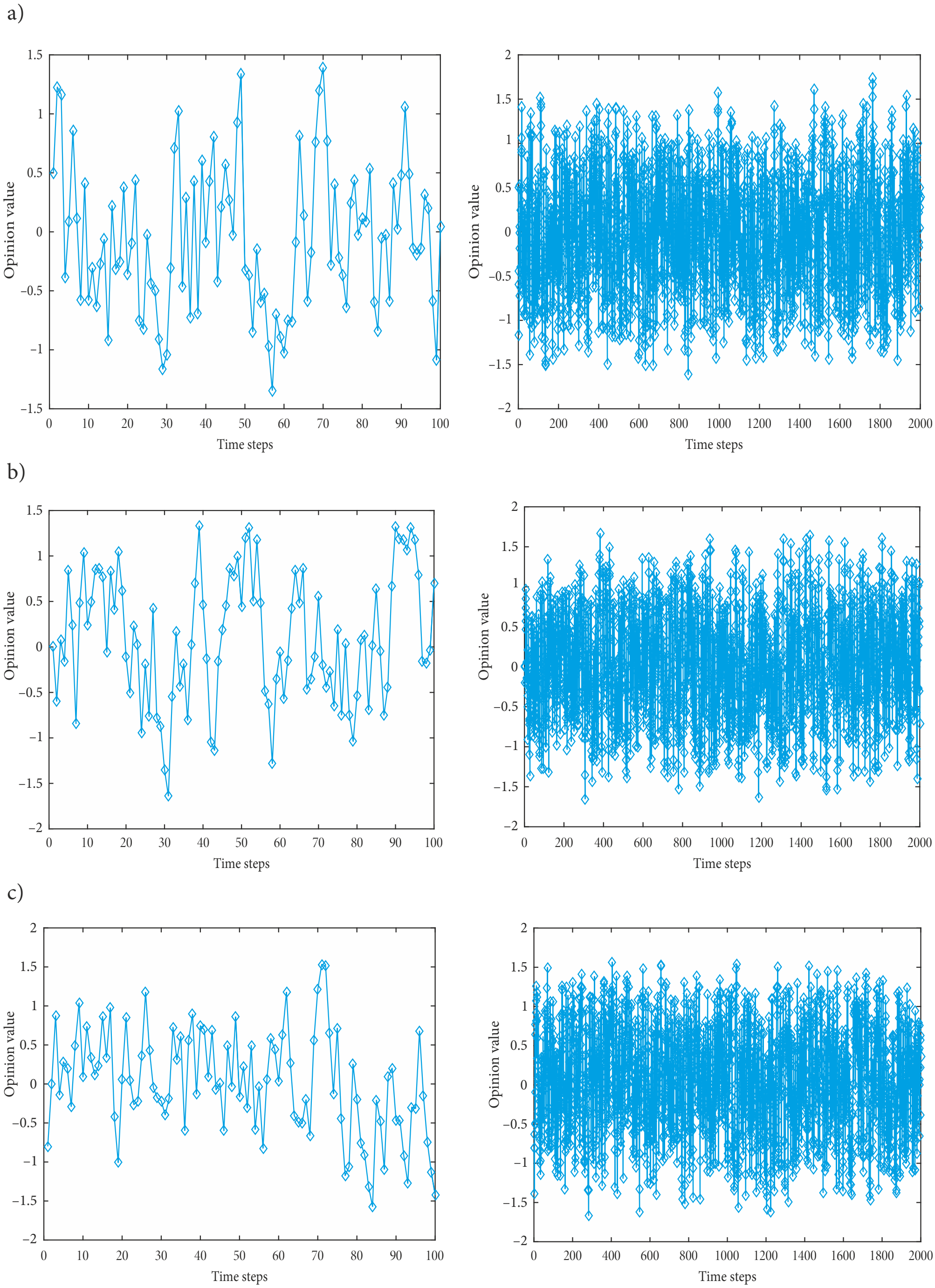

Figure 3. Process of opinion evaluation ($R_i = 1$): a) Original opinion is 0.5; b) Original opinion is 0; c) Original opinion is –0.8

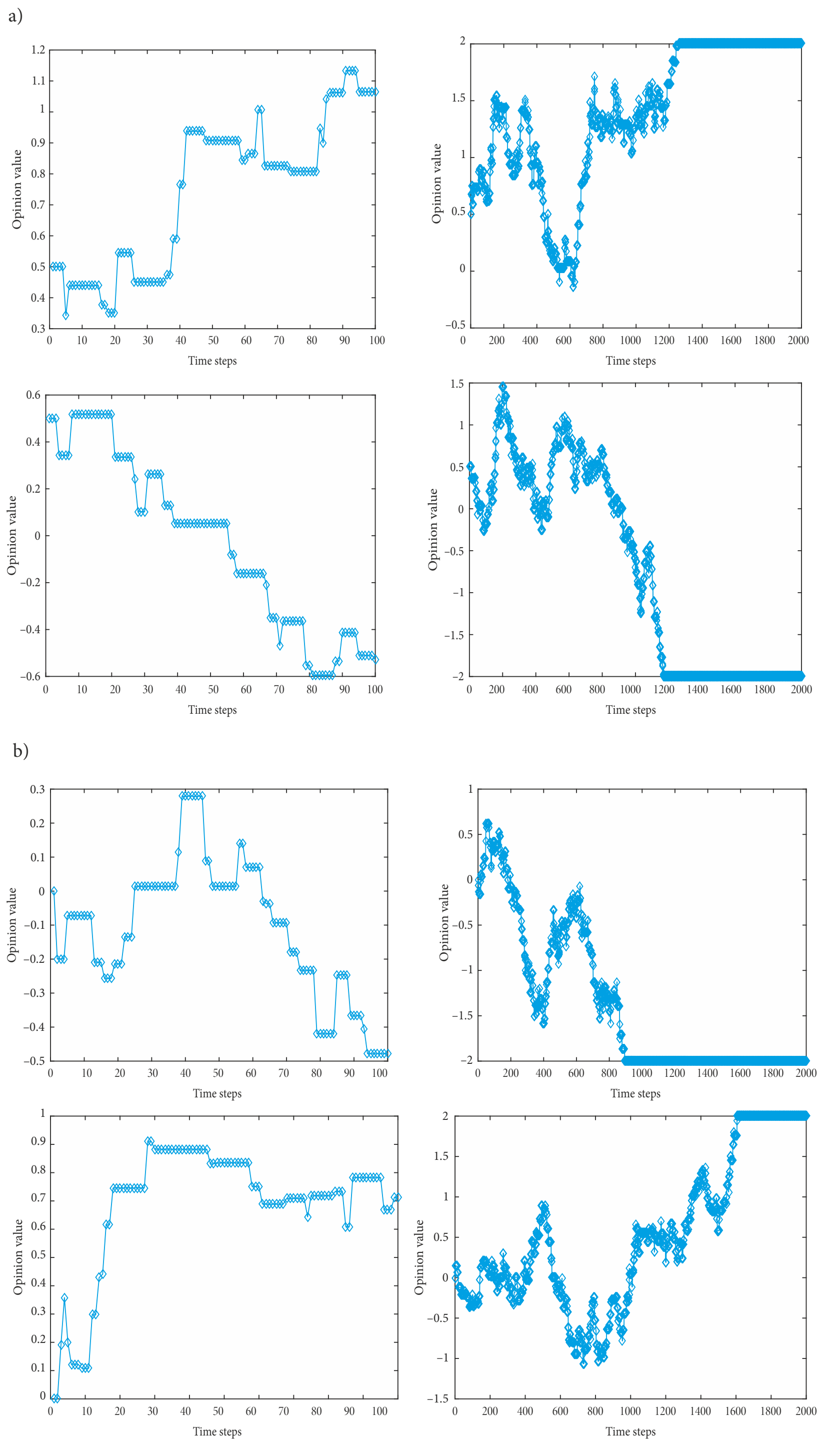

Figure 4. *To be continued*

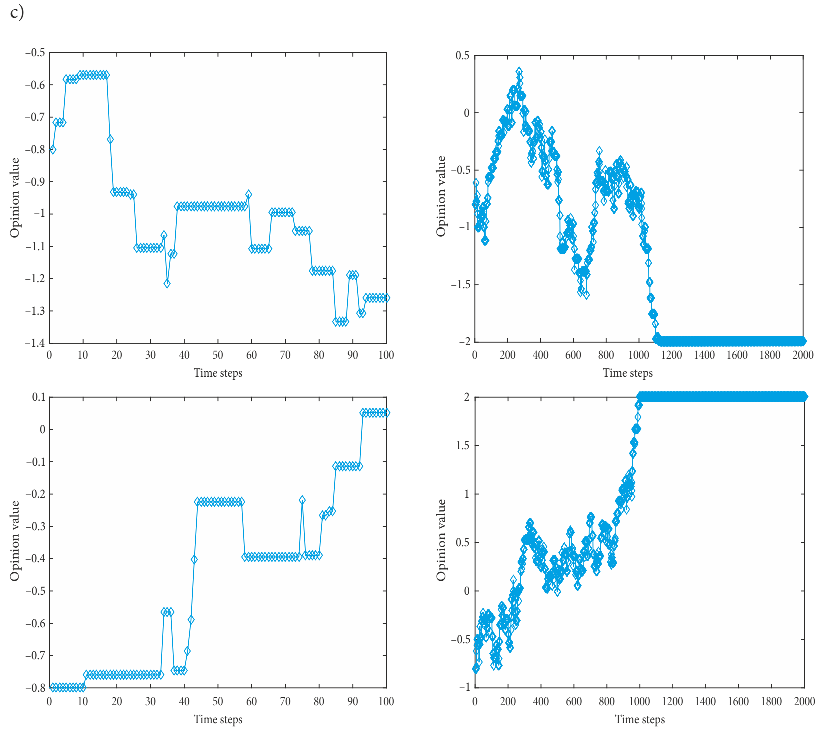

Figure 4. Process of opinion evaluation (R_i = 5): a) Original opinion is 0.5; b) Original opinion is 0; c) Original opinion is –0.8

In Figure 5, opinions of individuals with high membership levels (R_i = 9) are not affected by incoming online reviews. Their initial opinions remain stable, regardless of the number of online reviews. This shows that online reviews have little effect on individuals with higher membership-levels, who often make purchase decisions according to their original impression of a product.

To show the different effects of online product reviews on individuals with different membership levels, Figure 6 selected 30 random online reviews with different opinion values. The reason to choose 30 reviews is that consumers usually read only the first or last page of online reviews (about 30) before making a purchase decision (Cheung & Lee, 2012).

Figure 6 shows how individuals' purchase decisions were affected by online reviews. There are 30 randomly selected online reviews with different opinion values (range from –2 to 2) and 10000 randomly generated individuals with different membership levels, whose initial opinion is –0.8. The results show that at lower membership levels, individual opinion fluctuated depending on the contents of the online reviews, and will not remain in a stable state. Individual opinion will also fluctuate at medium membership levels but will remain stable and consistent with extreme opinion. Further incoming messages did not persuade them. Individual opinion fluctuates at high membership levels depending on the content of original opinions, which is slightly persuaded by the incoming message. With a low membership

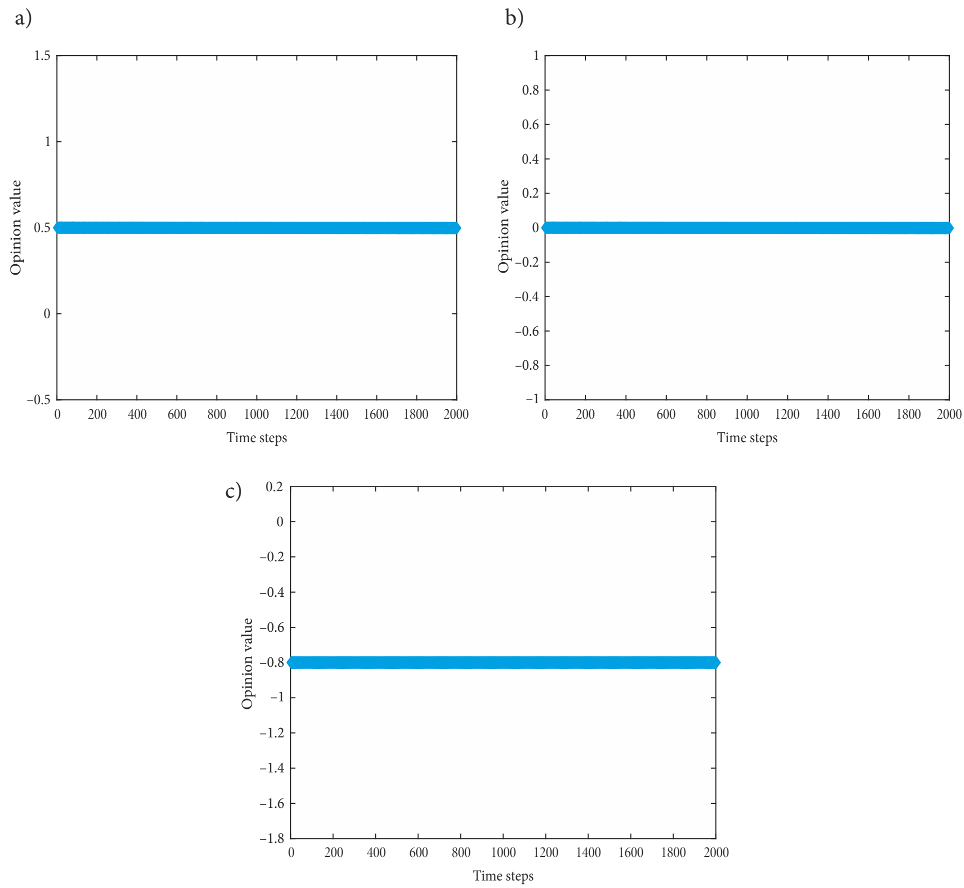

Figure 5. The process of opinion evaluation ($R_i = 9$): a) Original opinion is 0.5; b) Original opinion is 0; c) Original opinion is –0.8

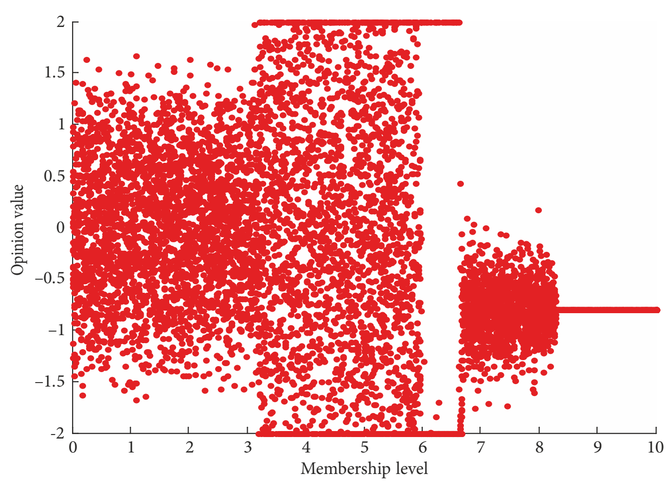

Figure 6. Individual opinion evaluations of 30 random online reviews

level, individual' persuasion knowledge is little, thus, individual can receive any information. However, with a medium or high membership level, individuals have more persuasion knowledge; they will subconsciously begin to accept a point of view that is consistent with the information, and ignore the messages that depart from their own point of view. Such behavior more easily leads to an opinion polarization (Deng et al., 2012).

4. Discussions

Online product reviews have important impacts on potential consumers' purchase decisions. Until now, no study has examined how consumers form their opinions dynamically under the influence of both positive and negative online product reviews.

This study proposes an opinion evaluation model based on the RAS model to analyze how online review valences affect individuals' opinion evaluation. The proposed model was utilized in the simulation to investigate the effects of online reviews on consumers with different membership levels. This study shows whole dynamic information processing in consumers purchase decision. Compared with previous study (using ELM (Park & Kim, 2008; Park & Lee, 2008) or HSM (Zhang et al., 2014)), only show the effect of eWOM on individuals purchase decision. This paper is better to understand the process of individuals' decision making affected by eWOM.

The findings of this paper can be summarized as follows: 1) Individuals with different membership levels often interact with online reviews differently. This result is similar to the Park and Kim (2008), Park and Lee (2008). 2) Though individuals with lower membership levels may be easily persuaded by incoming messages, they rarely achieve stable opinions, regardless the number of online reviews. Therefore, they cannot make easy and quick decisions when referencing online reviews. Prior study found that low involvement consumers are more likely to make their decisions based on the popularity of a product than reading reviews elaborately (Park & Lee, 2008). 3) Online reviews can persuade individuals at medium membership levels and they will reach stable states with extreme opinions after reading certain number of reviews. This stability enables them to make quick purchase decisions. 4) For consumers at higher membership levels, online reviews do not affect their opinions. They usually make purchase decisions based on their original impression of a product. Prior study shows that consumers with high involvement may use first several reviews to form their purchasing intention, and not use additional new reviews for their purchase decisions making (Park & Lee, 2008; Park & Kim, 2008).

There are three managerial implications of these results for e-commerce websites. First, classifying membership levels with the information sensitivity of potential consumers can be useful. The findings show that individuals with different membership levels have different sensitivities to product information. For instance, consumers with high expertise are likely early-adopters in the introduction stages of a product (Park & Kim, 2008). Businesses can target specific market segments and develop advertising strategies by considering these sensitivities appropriately.

Furthermore, as Park and Kim (2008), Park and Lee (2008) indicate potential consumers have different levels of expertise in product information. Our findings show that online reviews usually persuade individuals with low membership levels; however, they do not develop stable opinions of products. At medium membership levels, individuals often have extreme opinion of products. Therefore, businesses can mix positive and negative online reviews and render the latest positive reviews on priority. This can help consumers form positive opinions and make a quick purchase decision than they would otherwise.

Third, highlighting the ratio of positive and negative reviews for products can be beneficial. For medium level consumers, high positive to negative ratios can accelerate their process to form positive extreme opinions. Consumers with higher membership levels often make purchase decisions based on their initial opinions of products. Highlighting the ratio of positive to negative reviews can provide a comprehensive view of products in the introduction stage.

There are a couple of future research directions. First, this paper only considers the development of persuasion knowledge in membership level. In fact, there is always a development of persuasion knowledge in adoption of online reviews. Future study can further explore the impact of consumer persuasion knowledge on the adoption of online reviews. Second, this paper discusses the influence of online review with opinion evaluation. Future study can further explore individual preferences on online reviews using text analysis or sensitivity analysis.

References

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behaviour*. New York: Prentice Hall.

Banerjee, S., Bhattacharyya, S., & Bose, I. (2017). Whose online reviews to trust? Understanding reviewer trustworthiness and its impact on business. *Decision Support Systems*, *96*, 17-26. https://doi.org/10.1016/j.dss.2017.01.006

Babic, R., Sotgiu, F., De Valck, K., & Bijmolt, T. H. (2016). The effect of electronic word of mouth on sales: a meta-analytic review of platform, product, and metric factors. *Journal of Marketing Research*, *53*(3), 297-318. https://doi.org/10.1509/jmr.14.0380

Berger, J., Sorensen, A. T., & Rasmussen S. J. (2010). Positive effects of negative publicity: when negative reviews increase sales. *Marketing Science*, *29*(5), 815-827. https://doi.org/10.1287/mksc.1090.0557

Cai, Y., & Zhu, D. (2016). Fraud detections for online businesses: a perspective from blockchain technology. *Financial Innovation*, *2*, 20. https://doi.org/10.1186/s40854-016-0039-4

Chan, O., & Ma, A. (2016). Stochastic cost flow system for stock markets with an application in behavioral finance. *International Journal of Financial Engineering*, *3*(4), 1650026. https://doi.org/10.1142/S2424786316500262

Channel Advisor. (2011). Consumer survey: global consumer shopping habits. *Channel Advisor*, 2011.

Cheng, Y., & Ho, H. (2015). Social influence's impact on reader perceptions of online reviews. *Journal of Business Research*, *68*, 883-887. https://doi.org/10.1016/j.jbusres.2014.11.046

Cheung, C. M. K., & Lee, M. K. O. (2012). What drives consumers to spread electronic word of mouth in online consumer-opinion platforms. *Decision Support Systems*, *53*, 218-225. https://doi.org/10.1016/j.dss.2012.01.015

Cheung, M. K., & Thadani, R. (2012). The impact of electronic word-of-mouth communication: a literature analysis an integrative model. *Decision Support Systems*, *54*, 461-470. https://doi.org/10.1016/j.dss.2012.06.008

Cheung, M., Luo, C., Sia, C., & Chen, H. (2009). Credibility of electronic word-of-mouth: informational and normative determinants of on-line consumer recommendations. *International Journal of Electronic Commerce*, *13*(4), 9-38. https://doi.org/10.2753/JEC1086-4415130402

Deborah, R., John, C., & Whitney, Jr. (1986). The development of consumer knowledge in children: a cognitive structure approach. *Journal of Consumer Research*, *12*(March), 406-417.

Deffuant, G., Neau, D., Amblard, F., & Weisbuc, G. (2000). Mixing beliefs among interacting agents. *Advances in Complex Systems*, *3*, 87-98. https://doi.org/10.1142/S0219525900000078

Deng L., & Liu Y. (2011). Research on opinion formation and extremists modeling in internet virtual community. *Journal of Beijing Jiao Tong University*, *35*, 66-71.

Deng, L., Liu, Y., & Zeng, Q. (2012). How information influences an individual opinion evolution. *Physica*, *A 391*, 6409-6417. https://doi.org/10.1016/j.physa.2012.07.037

Dellarocas, C., Zhang, X., & Awad, N. (2007). Exploring the value of online product reviews in forecasting sales. *Journal of Interactive Marketing*, *21*, 23-45. https://doi.org/10.1002/dir.20087

Eagly, A. H., & Chaiken, S. (1993). *The psychology of attitudes*. Harcourt Brace Jovanovich College Publishers, Fort Worth, TX.

Eldomiaty, T., Rashwan, M., Din, M., & Tayel,W. (2016). Firm, industry and economic determinants of working capital at risk. *International Journal of Financial Engineering*, *3*(4), 1650031. https://doi.org/10.1142/S2424786316500316

Fazio, R. H. (1990). Multiple processes by which attitudes guide behavior: The MODE model as an integrative framework. *Advances in Experimental Social Psychology*, *23*, 75-109. https://doi.org/10.1016/S0065-2601(08)60318-4

Floyd, K., Freling, R., Alhoqail, S., Cho, H., & Freling, T. (2014). How online product reviews affect retail sales: a meta-analysis. *Journal of Retailing*, *90*(2), 217-232. https://doi.org/10.1016/j.jretai.2014.04.004

Filieri, R. (2015). What makes online reviews helpful? A diagnosticity-adoption framework to explain informational and normative influences in e-WOM. *Journal of Business Research*, *68*(6), 1261-1270. https://doi.org/10.1016/j.jbusres.2014.11.006

Fu, D., & Wang, K. (2013). Does customer membership level affect online reviews? A study of online reviews from 360buy.Com in China. *Proceedings – Pacific Asia Conference on Information Systems*, PACIS 2013 01/2013, 1-12.

Friestad, M., & Wright, P. (1994). The persuasion knowledge model: how people cope with persuasion attempts. *Journal of Consumer Research*, *21*, 1-31. https://doi.org/10.1086/209380

Hsu, C. L., & Liao, Y. C. (2014). Exploring the linkages between perceived information accessibility and microblog stickiness: the moderating role of a sense of community. *Information* & *Management*, *51*, 833-844. https://doi.org/10.1016/j.im.2014.08.005

Khare, A., Labrecque, L. I., & Asare, A. K. (2011). The assimilative and contrastive effects of word-of-mouth volume: an experimental examination of online consumer ratings. *Journal of Retailing*, *87*(1), 111-126. https://doi.org/10.1016/j.jretai.2011.01.005

Kim, D., Jang, S., & Adler, H. (2015). What drives café customers to spread eWOM?. *International Journal of Contemporary Hospitality Management*, *27*(2), 261-282. https://doi.org/10.1108/IJCHM-06-2013-0269

Kou, G., Ergu, D., Lin, C., & Chen, Y. (2016). Pairwise comparison Matrix in multiple criteria decision making. *Technological and Economic Development of Economy*, *22*(5), 738-765. https://doi.org/10.3846/20294913.2016.1210694

Kou, G., Peng, Y., & Wang, G. (2014a). Evaluation of clustering algorithms for financial risk analysis using MCDM methods. *Information Sciences*, *27*, 1-12. https://doi.org/10.1016/j.ins.2014.02.137

Kou, G., & Lin, C. (2014b). A cosine maximization method for the priority vector derivation in AHP. *European Journal of Operational Research*, *235*, 225-232. https://doi.org/10.1016/j.ejor.2013.10.019

Kou, G., Ergu, D., & Shang, J. (2014c). Enhancing data consistency in decision matrix: adapting Hadamard model to mitigate judgment contradiction. *European Journal of Operational Research*, (1), 261-271. https://doi.org/10.1016/j.ejor.2013.11.035

Kou, G., Lu, Y., Peng, Y., & Shi, Y. (2012). Evaluation of classification algorithms using MCDM and Rank Correlation. *International Journal of Information Technology* & *Decision Making*, *11*(1), 197-225. https://doi.org/10.1142/S0219622012500095

Kulakowski, K. (2009). Opinion polarization in tie Receipt-Accept-Sample Model. *Physica A: Statistical Mechanics and its Applications*, *2*(388), 469-476. https://doi.org/10.1016/j.physa.2008.10.037

Lee, J., Park, D., & Han, I. (2008). The effect of negative online consumer reviews on product attitude: an information processing view. *Electronic Commerce Research and Applications*, *7*, 341-352. https://doi.org/10.1016/j.elerap.2007.05.004

Lee, J., & Lee, J. N. (2009). Understanding the product information inference process in electronic word-of-mouth: an objectivity–subjectivity dichotomy perspective. *Information* & *Management*, *46*(5), 302-311. https://doi.org/10.1016/j.im.2009.05.004

Lee, K., & Koo, D. (2012). Effects of attribute and valence of e-WOM on message adoption: moderating roles of subjective knowledge and regulatory focus. *Computers in Human Behavior*, *28*, 1974-1984. https://doi.org/10.1016/j.chb.2012.05.018

Libai, B., Bolton, R., Bügel, M. S., Ruyter, K., Götz, O., Risselada, H., & Stephen A. T. (2010). Customer-to-customer interactions: broadening the scope of word of mouth research. *Journal of Service Research*, *13*(3), 267-282. https://doi.org/10.1177/1094670510375600

Liu, Y. (2006). Word of mouth for movies: its dynamics and impact on box office revenue. *Journal of Marketing*, *70*(7), 74-89. https://doi.org/10.1509/jmkg.70.3.74

Luo, C., Luo, X., Xu, Y., Warkentin, M., & Sia, C. (2015). Examining the moderating role of sense of membership in online review evaluations. *Information* & *Management*, *52*, 305-316. https://doi.org/10.1016/j.im.2014.12.008

Matlab. (2013). *Version 8.0* [Software]. Natick, MA: The Math Works Inc.

Muchnik, L., Aral, S., & Taylor, S. J. (2013). Social influence bias: a randomized experiment. *Science*, *341*, 647. https://doi.org/10.1126/science.1240466

Mukhopadhyay, B. (2016). Understanding cashless payments in India. *Financial Innovation*, *2*, 27. https://doi.org/10.1186/s40854-016-0023-z

Pang, B., & Lee, L. (2008). Opinion mining and sentiment analysis. *Foundations and Trends in Information Retrieval*, *2*, 1-135. https://doi.org/10.1561/1500000011

Park, D., & Kim, S. (2008). The effects of consumer knowledge on message processing of electronic word-of-mouth via online consumer reviews. *Electronic Commerce Research and Applications*, *7*(4), 399-410. https://doi.org/10.1016/j.elerap.2007.12.001

Park, D. H., Lee, J., & Han, I. (2007). The effect of on-line consumer reviews on consumer purchasing intention: the moderating role of involvement. *International Journal of Electronic Commerce*, *11*(4), 125-148. https://doi.org/10.2753/JEC1086-4415110405

Park, D., & Lee, J. (2008). eWOM overload and its effect on consumer behavioral intention depending on consumer involvement. *Electronic Commerce Research and Applications*, *7*(4), 386-398. https://doi.org/10.1016/j.elerap.2007.11.004

Petty, R. E., Tormala, Z. L., Briüol, P., & Jarvis, W. B. G. (2006). Implicit ambivalence from attitude change: an exploration of the PAST model. *Journal of personality and Social Psychology*, *90*, 21-41. https://doi.org/10.1037/0022-3514.90.1.21

Petty, R. E., & Cacioppo, J. T. (1984). Motivational factors in consumer response to advertisements. In W. Beatty, R. Geen, & R. Arkin (Eds.), *Human motivation* (pp. 418-454). New York: Allyn & Bacon.

Pietri, E. S., & Shook F. J. (2013). Weighting positive versus negative: the fundamental nature of valence asymmetry. *Journal of Personality*, *81*(2), 196-208. https://doi.org/10.1111/j.1467-6494.2012.00800.x

Ridings, C. M., Gefen, D., & Arinze, B. (2002). Some antecedents and effects of trust in virtual communities. *The Journal of Strategic Information Systems*, *1*(3), 271-295. https://doi.org/10.1016/S0963-8687(02)00021-5

Tee, H., & Ong, H. (2016). Cashless payment and economic growth. *Financial Innovation*, *2*, 4. https://doi.org/10.1186/s40854-016-0023-z

Ullah, R., Amblee, N., Kim, W., & Lee, H. (2016). From valence to emotions: exploring the distribution of emotions in online product reviews. *Decision Support Systems*, *81*, 41-53. https://doi.org/10.1016/j.dss.2015.10.007

Wang, X., Teo, H., & Wei, K. (2015). Simultaneity and interactivity of the effects of communication elements on consumers' decision making in eWOM Systems. *Journal of Electronic Commerce Research*, *16*(3), 153-174.

Wu, W., & Kou, G. (2016). A group consensus model for evaluating real estate investment alternatives. *Financial Innovation*, *2*, 8. https://doi.org/10.1186/s40854-016-0027-8

Wu, X., Wang, X., Ma, S., & Ye, Q. (2017). The influence of social media on stock volatility. *Frontiers of Engineering Management*, *4*(2), 201-211. https://doi.org/10.15302/J-FEM-2017018

Wu, J. (2017). Review popularity and review helpfulness: a model for user review effectiveness. *Decision Support Systems*, *97*, 92-103. https://doi.org/10.1016/j.dss.2017.03.008

Xia, H., & Hou, Z. (2016). Consumer use intention of online financial products: the Yuebao example. *Financial Innovation*, *2*, 18. https://doi.org/10.1186/s40854-016-0041-x

Ye, M., & Li, G. (2017). Internet big data and capital markets: a literature review. *Financial Innovation*, *3*, 6. https://doi.org/10.1186/s40854-017-0056-y

Zhang, Z. K., Zhao, J., Cheung, M. K., & Lee, K. O. (2014). Examining the influence of online reviews on consumers' decision-making: a heuristic-systematic model. *Decision Support Systems*, *67*, 78-89. https://doi.org/10.1016/j.dss.2014.08.005

Zaller, J. (2005). *The nature and origins of mass opinion* (pp. 32-44). Cambridge: Cambridge University Press.