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What motivates customers to publish online reviews promptly? A text mining perspective

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Abstract

Purpose – This work aims to explore why people review their experienced online shopping in such a manner (promptness), and what is the potential relationship between the users' review promptness and review motivation as well as reviewed contents.

Design/methodology/approach – To evaluate the customers' responses regarding their shopping experiences, in this paper, the "purchase-review" promptness is studied to explore the temporal characteristics of users' reviewing behavior online. Then, an aspect mining method was introduced for assessment of review text. Finally, a theoretical model is proposed to analyze how the customers' reviews were formed.

Findings – First, the length of time elapsed between purchase and review was found to follow a power-law distribution, which characterizes an important number of human behaviors. Within online review behaviors, this meant that a high frequency population of reviewers tended to publish relatively quick reviews online. This showed that the customers' reviewing behaviors on e-commerce websites may have been affected by extrinsic motivations, intrinsic motivations or both. Second, the proposed review-to-feature mapping technique is a feasible method for exploring reviewers' opinions in both massive and sparse reviews. Finally, the customers' reviewing behaviors were found to be mostly consistent with reviewers' motivations.

Originality/value – First, the authors propose that the "promptness" of users in posting online reviews is an important external manifestation of their motivation, product experience and service experience. Second, a semi-supervised method of review-to-aspect mapping is used to solve the data quality problem in mining information from massive text data, which vary in length, detail and quality. Finally, a huge amount of e-commerce customers' purchase-review promptness are studied and the results indicate that not all product features are responsible for the "prompt" posting of users' reviews, and that the platform's strategy to encourage users to post reviews will not work in the long term.

Keywords Online review, Review promptness, Motivation, Aspect, Text mining

Paper type Research paper

1. Introduction

The explosive growth of the Internet has created an ever-growing amount of content created by individuals, referred to as user generated content (UGC). One of the most common forms of UGC

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is online reviews, which is a form of customer feedback on e-commerce on online shopping sites (Tong, Wang, Tan, & Teo, 2013). Online reviews are often described as an accessible and frequently used form of electronic word of mouth (eWOM) (Duan, Gu, & Whinston, 2008; Trusov, Bucklin, & Pauwels, 2009). In the current e-commerce environment, online review is seen as a valuable and credible source of information concerning products' strengths and weaknesses (Qi, Zhang, Jeon, & Zhou, 2016; Yang, Liu, Liang, & Tang, 2019) that can help reduce uncertainty in purchase situations (Hu, Liu, & Zhang, 2008; Davis & Agrawal, 2018).

Today, many consumers are voluntarily sharing their product experience, however, from a cost-and-benefit analysis perspective; such a trend may not be rational (Tong *et al.*, 2013). Prior research published by Hu, Pavlou, and Zhang (2006) has provided evidence that online reviews may not be representative of the consensus due to under-reporting bias (Antioco & Coussement, 2018). These inspire us to propose the question as to what exactly motivates consumers to share information online. Researchers have studied a number of motivational factors, such as self-enhancement, social benefits and financial rewards, in an attempt to find out the customers' motivation to post reviews online (Bronner and de Hoog, 2011; Cheung & Lee, 2012; Tong *et al.*, 2013); some of them have studied why people post fake ones (Zhang, Zhou, Kehoe, & Kilic, 2016). A great deal of research has been devoted to investigating reviewers' motivations and how they are categorized with respect to information sharing, and meanwhile in practice, businesses are striving to grasp what influences customers to post reviews online (Cantallops & Salvi, 2014).

The study in Huang, Boh, and Goh (2017) has examined when and why online reviews from different sources and platforms influence a movie's box office over time and their analysis of existing literature on online review reveals two notable research gaps. First, the time interval (TI) of "purchase-review," i.e. the review promptness, does not receive enough attention in online review related research. In general, each customer's response was the result of the following events: First, the customer purchased a product online to meet his or her needs. Soon after that, he or she began to experience the service provided by the e-commerce platform (website), for example, the delivery. Next, the customer began to use the product that he or she had bought. Finally, the customer published a review online based on his or her own experience. Large-scale observations of actual reviewing behavior, even of reviewers who only write occasionally, provide several reasons why they may have wanted to write reviews (Brown, 2012). In other words, abovementioned four steps have led to an online review (See Figure 1). Among the many situations that promote a customer to write an online review, review promptness can uncover some information about the motivation for users to publish reviews online.

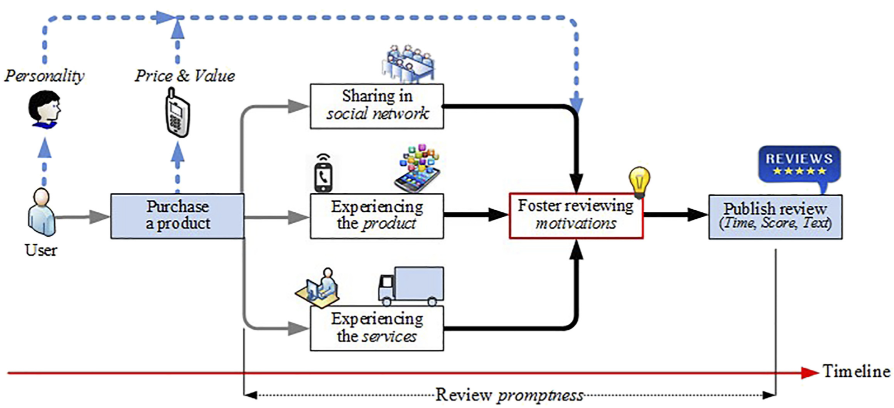

Figure 1.
Customer's behavior sequences in e-commerce

Second, the relationship between when to review (review promptness), why to review (review motivations) and what to review (review results) are not well studied. On one hand, it is hard to explore the customers' exact reviewing motivations directly because they usually do not explain why they post such a review online, especially for those extrinsic reasons (Kraut & Resnick, 2012). Therefore, the usual practice of inferring the review motivation is to observe the results of user reviews, i.e. the review valence (score) and the review opinion (text). On the other hand, the promptness with which the information is shared may reveal the customer's motivation involved in the review behavior. For example, if a customer feels offended, or if the staff involved in the online shipping process has been rude, they may react quickly by expressing their grievance or warning others (Brown, 2012). In one previous study, customers who did not write or post online travel reviews cited time constraints and simple lack of interest as the most common reasons (Gretzel, Yoo, & Purifoy, 2007). Promptness may also indicate the initiative and effort that the reviewers take to post reviews (Fu & Wang, 2013; Fu, Hong, Wang, & Fan, 2018), so reviewing text with specific contents at a particular point in time (for example, posted right after the purchase or after a long time) may suggest a specific motivation.

The purpose of this work is to fill in these gaps by exploring the effects of individual motivations on customers' review promptness in e-commerce website. Along this line, the following questions interact with each other and thus should be carefully addressed in e-business:

Q1. What motivates customers to publish reviews promptly in e-commerce website?

Q2. What is the relationship between the review promptness and the reviewed aspects?

Unlike most previous research, the focus of this work is on the review promptness of large numbers of online reviews. In detail, this work covers why people review their experienced online shopping in such a manner (promptness), and what the potential relationship between the users' review promptness and review motivation as well as reviewed contents is. To that end, the purchase-review behavior in a selected online market is studied firstly. Then, a theoretical model is used to analyze how the customers' reviewing motivations and the text of their reviews can affect the promptness of the customers' reviews. This paper has three main contributions: First, we propose that the "promptness" of users in posting online reviews is an important external manifestation of their motivation, product experience and service experience. Second, a semi-supervised method of review-to-aspect mapping is used to solve the data quality problem in mining information from massive text data, which vary in length, detail and quality. Finally, a huge amount of e-commerce customers' purchase-review promptness are studied and the results indicate that not all product features are responsible for the "prompt" posting of users' reviews, and that the platform's strategy to encourage users to post reviews will not work in the long term.

The rest of this paper is organized as follows. Section 2 describes the theoretical foundation and presents the research hypotheses. Section 3 sketches out the methodology and describes the approaches in detail. Section 4 shows the experimental results. Section 5 discusses the empirical results of the experiments.

Section 6 presents the conclusions.

2. Theoretical foundation and research hypotheses

Customers' reasons for sharing information have been studied extensively in literature. Most previous works have been devoted to what reviewers' motivations are and how they are categorized with respect to information sharing. The classic characterization of motivation, extrinsic or intrinsic, are used to discuss motivations to contribute to online communities, in which, intrinsic motivation is a drive to do something that is self-rewarding while extrinsic motivation is a drive to do something for external reasons (Ryan & Deci, 2000) (See Table 1 for some examples).

Notably, through in-depth interviews with Amazon reviewers and a six-month observation of the reviewer forums, Wu (2019) found that extrinsic motivation might crowd out or crowd in intrinsic motivation in different scenarios.

2.1 The effect of intrinsic motivations on review promptness

One of the major features of online shopping is that users make product purchase decisions based on online information (Tien, 2003). There is a consensus that product information is asymmetric in the transactional marketplace (Clarkson, Jacobsen, & Batcheller, 2007). However, the decision independence of different users in purchasing the same product allows some users to obtain information about the product before others. Obviously, this is an opportunity for preconsumers of a product to help others.

The primary means to help others is to provide better product information to eliminate decision uncertainty (Zhu, 2004) or reduce potential transaction risk (Cheng, Courtenay, & Krishnamurti, 2006). Accordingly, if the main concern of a reviewer is to help other people make better decisions or reward a company for a good product, he or she may recount his or her experiences carefully and provide very detailed information (Lu, Tsaparas, Ntoulas, & Polanyi, 2010). This is especially true of product update (Kwark, Chen, & Raghunathan, 2014). Detailed information about the product is considered useful (Li, Huang, Tan, & Wei, 2013; Liu & Park, 2015) and is widely welcomed by subsequent users. In contrast, an (extremely) negative rating from a consumer can be of great concern to others, both in terms of reminding subsequent consumers of the risks of the transaction and venting their frustrations (Vinson, Dale, & Jones, 2019). Because posting an information-rich review takes effort, the following hypothesis can be expected:

H1. The focus of the user experience on product features will have a positive impact on review promptness.

Some customers are highly pleased with the online shopping experiences and want to share the experience with others. Other customers are not satisfied with the quality of the product or service, so they would like to express their grievances as soon as possible, often with the desire to negatively affect sales (Li, Wu, & Mai, 2019). Consequently, extremely angry or happy customers may have stronger desires to write reviews quickly to criticize or praise the transaction. For example, a customer has been offended or if staff involved in the online shopping process has been rude, people may take a quick reaction to express a grievance or warn others (Brown, 2012).

Type	Motivation (main references)
Intrinsic	*Enjoyment in helping others* (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004; Gretzel *et al.*, 2007; Bronner and de Hoog, 2011; Cheung & Lee, 2012; Tong *et al.*,2013) *Expression of feelings*: Negative (Hennig-Thurau *et al.*, 2004; Gretzel *et al.*, 2007); Positive: (Jeong & Jang, 2011)
Extrinsic	*Getting financial rewards or reciprocal benefits* (Hsu & Lin, 2008; Jiacheng, Lu, & Francesco, 2010) *Getting reputational advantages or social benefits* (Hennig-Thurau *et al.*, 2004; Bronner and de Hoog, 2011; Gretzel *et al.*, 2007) *Helping the company* (Hennig-Thurau *et al.*, 2004; Gretzel *et al.*, 2007; Bronner and de Hoog, 2011; Jeong & Jang, 2011)

Table 1.
Customer's motivations for sharing online

However, recent evidence suggested that online word-of-mouth were overwhelmingly positive (Hu, Zhang, & Pavlou, 2009), i.e. most products have received 5-star ratings (extremely good). Further, as the number of product reviews increases, the problem of information overload will inevitably arise (Fen Hu and Krishen, 2019; Jin, Zhangwen, & Naichen, 2019). With this information overload and many positive sentiments already posted, competition among reviewers (previously consumers) for the attention of review recipients has become more intense (Shen, Hu, & Ulmer, 2015; Iyer & Katona, 2016). Since the similar positive reviews are less likely to catch the attention of more subsequent potential consumers (Lu, Wu, & Tseng, 2018), there is less incentive for those consumers to post such reviews in a timely manner. In contrast, an (extremely) negative rating and score from a consumer can attract significant attention from others, both in terms of notifying subsequent consumers of the risks of the transaction and in terms of venting their frustrations (Vinson *et al.*, 2019; Liu *et al.*, 2020). Therefore, we propose the following hypothesis:

H2. Positive rating has a negative impact on review promptness.

2.2 The effect of extrinsic motivations on review promptness

2.2.1 Personal gain. Social exchange theory is one of the basic theories of social economy (Cook & Rice, 2006) that attempts to explain the individual behavior of participation in the exchange of resources. According to the theory, if one person provides advice based on his or her knowledge, then he or she expects certain types of social rewards, such as approval, respect or increased status in the eyes of the other individuals (Wasko & Faraj, 2005). This type of motivation is related to reviewer's personal gain, such as social (community) status and financial reward (Dellarocas, Gao, & Narayan, 2010). Most Business-to-Customers (B2C) websites tend to classify their customers using different membership levels (Fu *et al.*, 2018) where the higher-level users have chances to gain more benefits and rewards than others. This can motivate the lower-level customers to publish reviews quickly to increase their membership level. Membership and level management strategy are used to provide customers with not only online review communities but also incentives that reward them for posting reviews online (Mudambi & Schuff, 2010). It is reasonable to hypothesize the following:

H3. Membership level has a positive impact on review promptness.

Hennig-Thurau *et al.* (2004) were the first to have reported platform assistance as a motivation to engage in eWOM. This motivation is that the creators of the online reviews believe that by posting the reviews they can get active support in solving their problems. Because this motivation is not mentioned in other studies, and the platform assistance motivation is not applicable to the report about UGC proposed in this study, it will not be used. Generally, in a B2C business process, service quality and purchasing experience in e-service quality are regarded as dominant customer satisfaction factors (Subramanian, Gunasekaran, Yu, Cheng, & Ning, 2014). As can be experienced by consumers, three types of service can be perceived by the buyer: service from the producer, the platform (seller) and the delivery.

In a traditional business, if customers have any positive or negative feelings about the shopping process, they tend to express them directly to management in person. Similarly, in online businesses, the performance of e-commerce platform (online shopping system) can also be an object of review (Cho, Im, Hiltz, & Fjermestad, 2002). By considering the customers' desire to express positive or negative feelings, the following can be proposed:

H4. The experienced service of e-commerce platform has a negative impact on review promptness.

Logistics is very important for e-commerce to bridge the physical distance between end-users and their online purchases (Ramanathan, George, & Ramanathan, 2014), and studies show that for e-retailers to be competitive, they must pay more attention to product delivery (logistics) than other intangible service quality factors (Subramanian *et al.*, 2014), because it will directly affect user satisfaction (Hu, Huang, Hou, Chen, & Bulysheva, 2016) and even repeat purchases (Jain, Gajjar, & Shah, 2021), and will of course be the factor that inspires users to post relevant comments quickly or casually. In the e-commerce field, users are concerned about many aspects of the logistics, usually including the speed of delivery service (Cherrett *et al.*, 2017), service attitude, and the company's quick response when problems arise during delivery (Chen, Hsu, Hsu, & Lee, 2014). In this study, we expect to uncover clues from the text of users' comments about their promptness in posting reviews. For this reason, the following hypothesis is made:

H5. The experienced service of logistics has a negative impact on review promptness.

In reality, a person's decision to buy a product is often strongly influenced by his/her friends, acquaintances and business partners rather than by strangers (Kim & Srivastava, 2007; Grange & Benbasat, 2010). Therefore, we analyze the impact of online social relationships on users' posting of "prompt" reviews from the following perspectives. Firstly, as observed by Bearden, Calcich, Netemeyer, and Teel (1986), there are two kinds of social influence in the adoption of a new product. The first is normative social influence that creates social pressure for people to adopt a product for fear of being treated as old fashioned, regardless of their actual preference. The second is informational social influence. Secondly, previous research has found that most review sites or sites with a review function has evolved into virtual communities to which many participants develop a sense of emotional belonging (Koh, Kim, & Kim, 2003; Kim, Lee, & Hiemstra, 2004). The need of belongingness is one of the fundamental drives of human beings, which motivate people to interact and maintain social bond in order to be satisfied (Cai & Chau, 2015). Therefore, publishing reviews online is motivated by the belongingness to existing online product or review community (Luo, Luo, Xu, Warkentin, & Sia, 2015). Moreover, Huang (2011) explained that over time, the visibility of contributors (in the product community) and the popularity of their stories can lead to an increase in their social impact. In short, to maintain a sense of belonging in the product community may also be one of the contributing factors for users to actively post comments. For these reasons, the following was hypothesized:

H6. Social effect has a negative impact on review promptness.

The above research model is shown in Figure 2.

3. Data set

In this section, we will detail the data used in this work. Particularly, the Latent Dirichlet allocation (LDA) method was used to mining the reviewed aspects.

3.1 Data collection

In this work, the review data were drawn from the product category of mobile phone in www.jd.com website, which is one of the most famous B2C online shopping malls in China.

In this study, we crawled a total of 487,817 reviews of 71 mobile phone products in the market. The contents listed in Table 2 include all the original data. All the review data extracted online are denoted by C, for the i-th review data c_i in C, the reviewing information is summarized in Table 2.

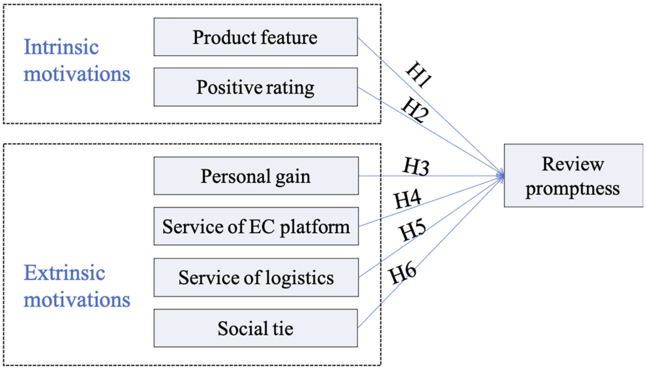

Figure 2.
Research model

Table 2.
Important information extracted in an online review c_i

Attribute	Description	Denotation
USER ID	Customer ID	$c_i(ID)$
MEMBERSHIP LEVEL	Customer membership	$c_i(ML)$
PURCHASE TIME	Time of online purchase	$c_i(PT)$
SCORE	Rating of the product left by a customer	$c_i(SC)$
REVIEW	Contents of customer's review	$c_i(RE)$
REVIEW TIME	Time of online review	$c_i(RT)$

Table 3 shows a description of the data set. The distribution of review data is observed in all type of characters, especially, the averaged time elapsed from purchase to review was small, 24.59 (days). Moreover, the average length of review text was also extremely short, an average of 33.78 Chinese characters.

3.2 Review aspects mining

Based on the previous theoretical assumptions, our focus is on the information about the features of those products that users have reviewed. In other words, we want to know what product-related features are covered by the content of a particular review. To this end, we try to identify the key factors that consumers care about the most regarding the product they have bought (Jia, 2020). Therefore, the focus of this paper is not fine-grained text mining. Instead, considering that user reviews are textual data, we adopt the LDA method commonly used in review mining research to extract the topics of user reviews (Kim & Kang, 2018; Zhang, 2019).

Table 3.
Descriptions of the data set

Characters	Min	Max	Ave	Std
Level of reviewer's membership	1	5	3.548	0.96
Rated score	1	5	4.65	0.85
Price (Yuan)	59	4,699	930.1	1068.32
Purchase-review interval (days)	0	183	24.59	35.87
# of reviews for each product	14	28,462	6870.66	7440.62
Length of review (# of Chinese characters)	2	1,265	33.78	28.68

In the literature of natural language processing, LDA is an appropriate method for such tasks, as it allows sets of observations to be explained by unobserved groups so as to explain why some parts of the data are similar (Blei, Ng, & Jordan, 2003). For example, if observations are words collected into documents, it posits that each document is a mixture of a small number of topics and that each word's creation is attributable to one of the document's topics.

For the i-th review, $c_i, (i = 1, \ldots, |C|)$, we first split it into words and remove the noise and meaningless terms, and then we get a combination of words and phrases as follows:

$$c_i = \{w_{i1}, \ldots, w_{ij}, \ldots\}.. \tag{1}$$

Next, the LDA algorithm can be conducted on the data set of $C = \{c_i\}$ to generate a set of topics $A = \{A_j\}$ and A_j can be specified as follows:

$$A_j = \{a_{j1}, \ldots, a_{jk}, \ldots\}, \tag{2}$$

where a_{jk} denotes the k-th feature associated with aspect A_j. In this way, we can study whether an online review c_i contains a topic of A_j by examining the composition of c_i and A_j. Therefore, the next experimental task is to obtain the topics of all online reviews by LDA.

However, as an unsupervised method, the number of targeted aspects is hard to be determined in LDA. In this work, the number of aspects/topics was set from 10 to 100 from the start, and a measure of perplexity is then introduced to identify the most suitable number of aspects (Wallach, Murray, Salakhutdinov, & Mimno, 2009). Perplexity is a measurement of how well a probability distribution or probability model predicts a sample. To avoid the bias of the sampling process in the LDA algorithm and to keep the calculation results robust and stable, the experiments of perplexity were performed 3 times (from test 1 to test 3). The experimental results are shown in Figure 3. Note that, if the number of aspects is chosen too large, more information can be retained, but this will make the information obtained for each topic too fragmented (a relevant topic is split into multiple subtopics). It will be difficult to interpret the results obtained based on such data in the subsequent analysis. Conversely, if the number is chosen too small, each topic may be the result of aggregation of several independent topics. Figure 3 shows that the computational results and trends of the LDA algorithm on our dataset are relatively stable, and in particular, 10–30 may be the appropriate area for determining a topic number and finally 20 was selected for the experiments.

Inspired by previous studies of feature selection in text mining (Pontiki *et al.*, 2014; Xiao, Wei, & Dong, 2016), after manual inspection, mining results were gathered on seven aspects (See Table 4). They are four product-related aspects (i.e. appearance, function, system, value), 2 platform-related aspects (i.e. service, logistics) and 1 socially related aspect (i.e. social ties).

As such, we can find the distribution of the reviewed product aspects over time (as shown in Figure 4). As we can see in the figure, overall, these product-related topics are mentioned steadily in user reviews from the first day of sale to day 600 (with a downward trend in System topics); the change (oscillation) in the proportion of product topics in reviews posted between days 600 and 1,000 is very dramatic. In addition, the function-aspect gained and sustained a high number of reviews, and the appearance- and value-aspect gained a fair proportion of review content. Both platform- and socially-related aspects showed an oscillatory proportion from 600–1,000 days, and the appearance-aspect had a relatively high number of reviews. However, the relative number of reviews that included system aspects declined continuously over time.

4. Empirical analysis

In this section, a theoretical model is constructed to evaluate the factors that affect customers' reviewing behavior, in particular, promptness.

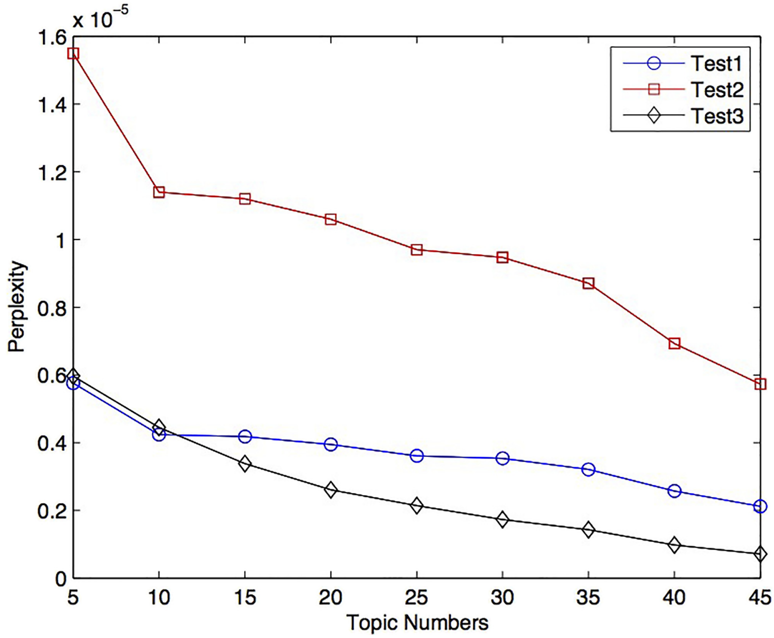

Figure 3.
The perplexity of mined aspects

Table 4.
Reviewed aspects in online reviews

Aspects (A_j)	Top-5 features ($a_{jk}, k = 1, \ldots, 5$)
Appearance	Screen, Newness, Appearance, Color, Beautiful
Function	Call, Function, Complete, Photography, Operation
System	Apple, Smooth, Stable, Android, Symbian
Value	Price, Cost performance, Economical, Cheap, Worth
Service	Authentic product, Shopping, JingDong(APP), Invoice, Shopping Mall
Logistics	Delivery, Logistics, Package, Seal Film, Delivery speed
Social tie	Uncle, Father, Old people, Mother, Friends

4.1 Dependent variable

The dependent variable is the "purchase-review" *TI* which is measured by the difference between the reviewing time and purchasing time. For review c_i, TI_i is calculated as follows:

$$\mathrm{TI_i} = \mathrm{c_i(RT)} - \mathrm{c_i(PT)}.. \tag{3}$$

Among the 487,817 reviews, all the values of TI_i were power-law distributed.

4.2 Independent variables

Based on the mined aspects, the contents of the reviews were organized using 7 binary variables valued as "1" if mentioned in a review and "0" if otherwise. All the independent variables used were summarized in Table 5.

On www.jd.com, all registered users are divided into 5 levels from low to high, i.e. New (Iron), Bronze, Silver, Gold, and Diamond members. In this way, the variable of *membership* is mapped onto the score level from "1" (low) to "5" (high). Figure 5(a) illustrates the

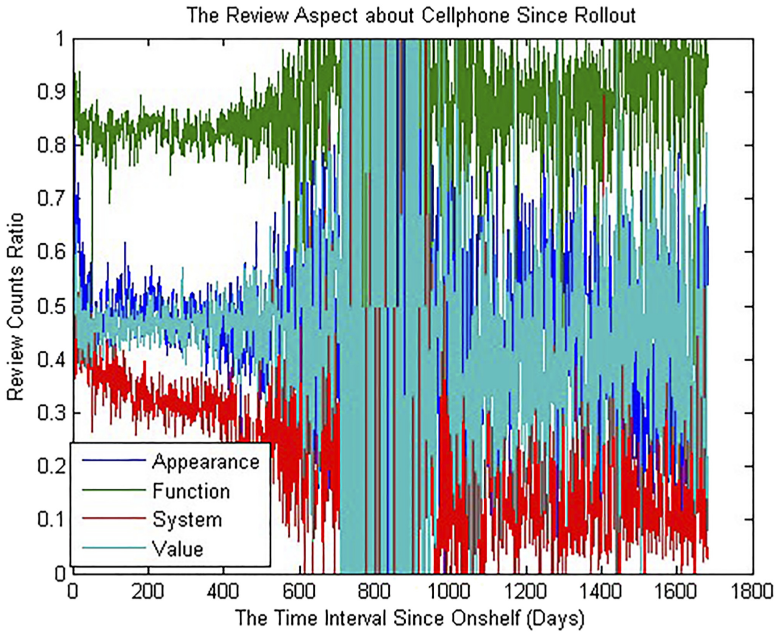

Figure 4.
Distribution of the reviewed aspects for products

Table 5.
Variables and explanations

Variable	Explanation
Rating	The rated score
Member	Membership of a reviewer in an commerce system
Appearance	1 for appearance aspect reviewed, otherwise 0
Function	1 for function aspect reviewed, otherwise 0
System	1 for system aspect reviewed, otherwise 0
Value	1 for value aspect reviewed, otherwise 0
Service	1 for service aspect reviewed, otherwise 0
Logistics	1 for logistics aspect reviewed, otherwise 0
SocialTie	1 for social aspect reviewed, otherwise 0

distributions of *membership* in the data set. However, www.jd.com provides the 1 (bad)-to-5 (excellent) star rating systems to users for any of the products they purchased. As shown in Figure 5(b), the distribution of *score* is skewed to the right. This is consistent with previous works showing that the distribution of user ratings tends to be right skewed (Hu *et al.*, 2006), with most products rated as a 4 or 5. It was here treated as log(*score*) in the regression model.

4.3 Control variables

The results of previous studies in the literature of online review have shown that some personal gains can be drawn from conspicuous consumption, which denotes the act of buying many things, especially expensive things, in a way that attracts people's attention (Bagwell & Bernheim, 1996; O'Cass & McEwen, 2004). For this reason, the average price of each product was used as the control variable in this work.

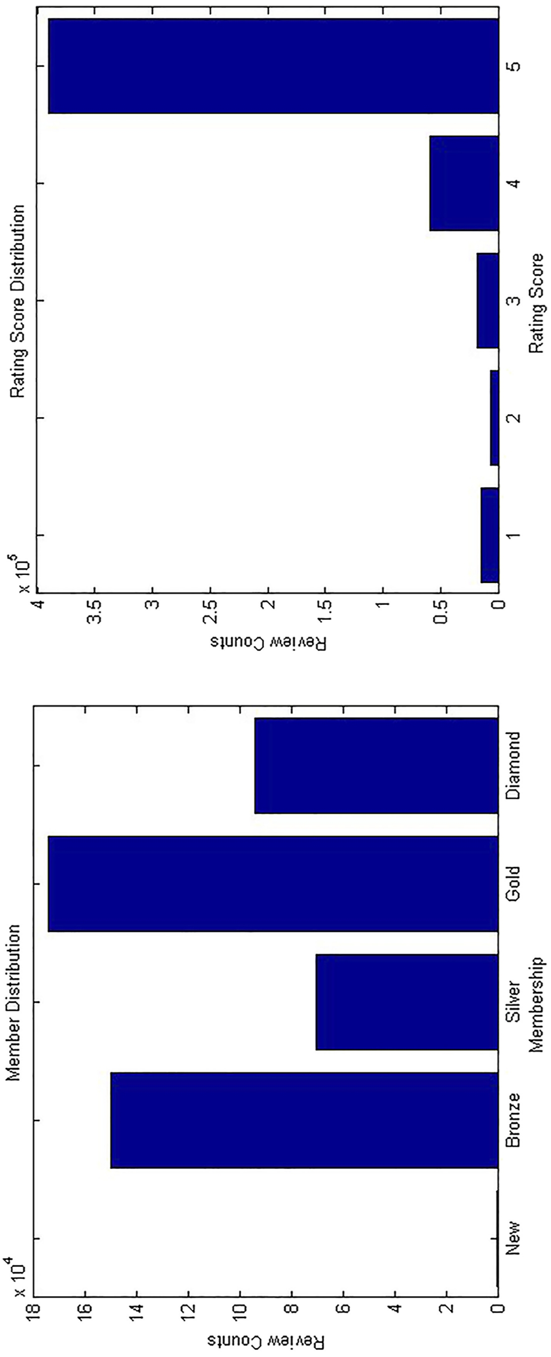

Figure 5.
Distributions of *membership* and *score* in the data set

The average online price for each product was calculated to confirm the presence of conspicuous consumption in a B2C shopping system. In the collected data set, the distribution of average *price* was also skewed to the left (Figure 6), so it was treated as log(*prices*) in the model.

Finally, Table 6 provides the statistical description for all the variables of the data set.

4.4 Model specification

In order to test the hypotheses proposed above, a linear specification was used to estimate reviewers' purchase-review TI.

$$\log(TI+1) = \alpha + \beta_1 \log(Rating) + \beta_2 Member + \beta_3 Member^2 + \beta_4 Service + \beta_5 Logistics + \beta_6 Appearance + \beta_7 Function + \beta_8 System + \beta_9 Value + \beta_{10} SocialTie + \beta_{11} \log(Price) + \varepsilon. \tag{4}$$

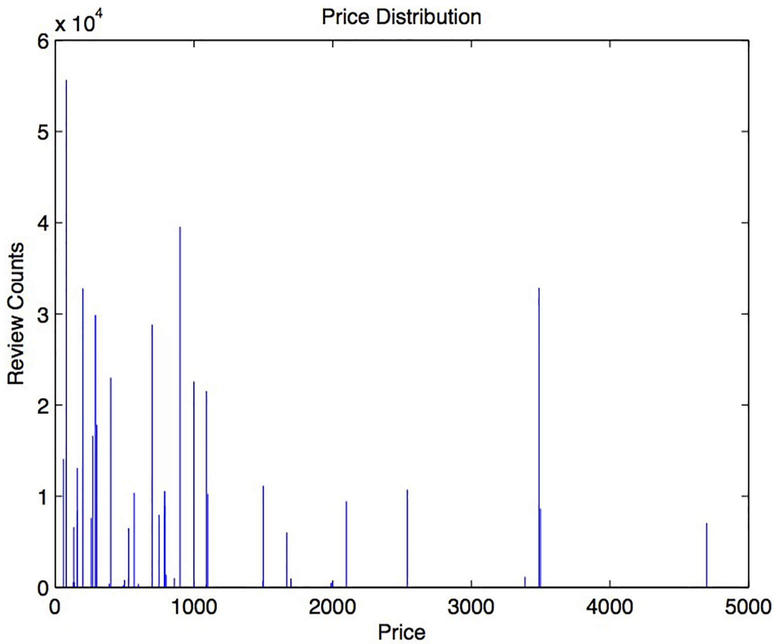

Figure 6. Distributions of *price* (Yuan) in the data set

	Obs	Mean	Std. Dev	Min	Max
log(TI + 1)	487,817	2.436	1.2725	0.000	5.215
log(Rating)	487,817	1.505	0.3008	0	1.609
Member	487,817	3	0.9588	1	5
Member^2	487,817	9	6.8931	1	25
log(Price)	487,817	6.342	1.1738	4.078	8.455

Table 6. Descriptive statistics for the variables

The dependent variable of $\log(TI + 1)$ is used here to avoid zero values during calculation. In addition, a nonlinear relationship between the *Member* and review promptness was expected. This relationship was modeled by including the *Member* as both a linear term (*Member*) and a quadratic term ($Member^2$). The linear term was expected to be positive and the quadratic term negative, indicating an inverted U-shaped relationship (Mudambi & Schuff, 2010), and that those reviewers with very low and very high membership level tended to post quick reviews after purchases.

In order to ensure that the regression setup leads to satisfactory results, initially, a correlation analysis was conducted to confirm the correlations of corresponding variables in order to avoid multicollinearity. Correlation values shown in Table 7 indicate the acceptable levels of correlation.

Analyzing results from the big data showed all the variables to be correlated to each other ($p < 0.05$) and the maximum correlation index to be about 0.9907 (correlation between *Member* and $Member^2$). However, the correlations between the different independent variables were very low (the second biggest index was 0.2927 existing between *SocialTie* and log*Price*).

4.5 Empirical results

The results of the regression analysis for the model are shown in Table 8. The residual standard error is 1.247 on 487,805 degrees of freedom the adjusted R-squared is 0.040. The F-statistic is 1825 on 11 and 487,805 degrees of freedom, the value of $Pr(> |t|)$ is less than $2.2e - 16$.

As proposed here, despite of the variable of $Value(\beta_9 = -0.009753)$ drawn from the reviewed aspects, all the other variables had statistically significant effects on $\log(TI + 1)$. These variables explained about 4% of the logarithm of reviewers' purchase-review TI ($R^2 = 0.040$).

As shown in Table 8, *Member*, *Function* and *SocialTie*, had positive effects on the logarithm of reviewers' TI, which means that along with a longer TI, the following is true: (1) People with high-level memberships tended to publish very brief reviews online or not to post reviews at all. This is mainly because once a customer reaches the highest level of membership; the reward mechanism of the e-commerce system no longer provides any incentive. (2) If the intent is to comment on a functional aspect of a cell phone, the reviewer may need time to interact with the product before any thoughtful evaluation is made. (3) The results concerning social tie pressure can be very different from hypothesis 5. By rechecking the review contents, we can find that, lots of cell phones were bought as a gift for another person. Under such a situation, the reviewers need more time to wait for the feedback from the end-users to publish the review.

In contrast, *log*(*Rating*), $Member^2$, *Appearance* and *System* showed negative effects on $\log(TI + 1)$. This indicates the following: (1) Under the behavior of quick reviewing, a relatively high score would be assigned by the user. (2) People with low-level memberships tended to publish quick reviews to elevate their rank in the e-commerce platform. Simultaneously, people with very high-level memberships also published quick reviews after purchase, but they did so in a perfunctory way. As shown in Figure 7, the average lengths of review text post by the "New" and "Diamond" level people (purchase-review interval was 0–25 days) were significantly shorter than those posted by others. (3) Reviews posted after a short purchase-review TI tended to mention *Appearance* and *System* more than other topics, probably because these can be assessed quickly.

Interestingly, *Service* and *Logistics*, both related to the e-commerce platform itself, showed negative effects on $\log(TI+1)$. This indicates that service directly from the e-commerce system tends to suffer from a quick response. Service, especially delivery, is an important

Table 7. Correlation analysis

	log(Rating)	log(TI+ 1)	Mem.	Mem.^{2}	Serv.	Logist.	Appear	Func.	Sys.	Value	Social	log (Price)
log(Rating)	1.0000	−0.0629	0.0477	0.0472	−0.0219	−0.0084	0.0130	−0.0041	0.0164	0.0473	0.0751	0.0564
log(TI+ 1)	−0.0629	1.0000	0.0248	0.0218	−0.0306	−0.1595	−0.0588	0.0050	−0.0346	−0.0119	0.0538	−0.0997
Mem.	0.0477	0.0248	1.0000	0.9907	−0.0143	−0.0218	0.0047	0.0063	0.0166	−0.0041	0.0033	0.0999
Mem.^{2}	0.0472	0.0218	0.9907	1.0000	−0.0142	−0.0216	0.0027	0.0054	0.0146	−0.0042	0.0035	0.0936
Serv.	−0.0219	−0.0306	−0.0143	−0.0142	1.0000	0.0880	0.0222	0.0272	0.0389	0.0292	−0.0590	0.0585
Logist.	−0.0084	−0.1595	−0.0218	−0.0216	0.0880	1.0000	0.0375	−0.0061	0.0333	0.0313	−0.0891	0.1126
Appear	0.0130	−0.0588	0.0047	0.0027	0.0222	0.0375	1.0000	0.1493	0.0767	0.0037	−0.0568	0.2042
Func.	−0.0041	0.0050	0.0063	0.0054	0.0272	−0.0061	0.1493	1.0000	0.1247	0.0347	0.0247	−0.0350
Sys.	0.0164	−0.0346	0.0166	0.0146	0.0389	0.0333	0.0767	0.1247	1.0000	0.0162	−0.0831	0.2138
Value	0.0473	−0.0119	−0.0041	−0.0042	0.0292	0.0313	0.0037	0.0347	0.0162	1.0000	−0.0303	−0.0105
Social	0.0751	0.0538	0.0033	0.0035	−0.0590	−0.0891	−0.0568	0.0247	−0.0831	−0.0303	1.0000	−0.2927
log (Price)	0.0564	−0.0997	0.0999	0.0936	0.0585	0.1126	0.2042	−0.0350	0.2138	−0.0105	−0.2927	1.0000

Note(s): *$p < 0.05$

Table 8.
Results of regression analysis

	Estimate	Std.Error	*t* value	*Pr*(> |*t*|)	
(Intercept)	2.859996	0.026657	107.289	<2e−16	***
log(Rating)	−0.266418	0.005988	−44.490	<2e−16	***
Member	0.272334	0.013704	19.873	<2e−16	***
Member^2	−0.032416	0.001905	−17.018	<2e−16	***
Service	−0.031410	0.003601	−8.723	<2e−16	***
Logistics	−0.557926	0.005395	−103.423	<2e−16	***
Appearance	−0.097599	0.003704	−26.348	<2e−16	***
Function	0.028081	0.004914	5.715	1.10e−08	***
System	−0.030743	0.004023	−7.642	2.15e−14	***
Value	−0.009753	0.003594	−2.714	0.00665	**
SocialTie	0.062638	0.004235	14.792	<2e−16	***
log(Price)	−0.071637	0.001681	−42.615	<2e−16	***

Note(s): *p < 0.05; **p < 0.01; ***p < 0.001

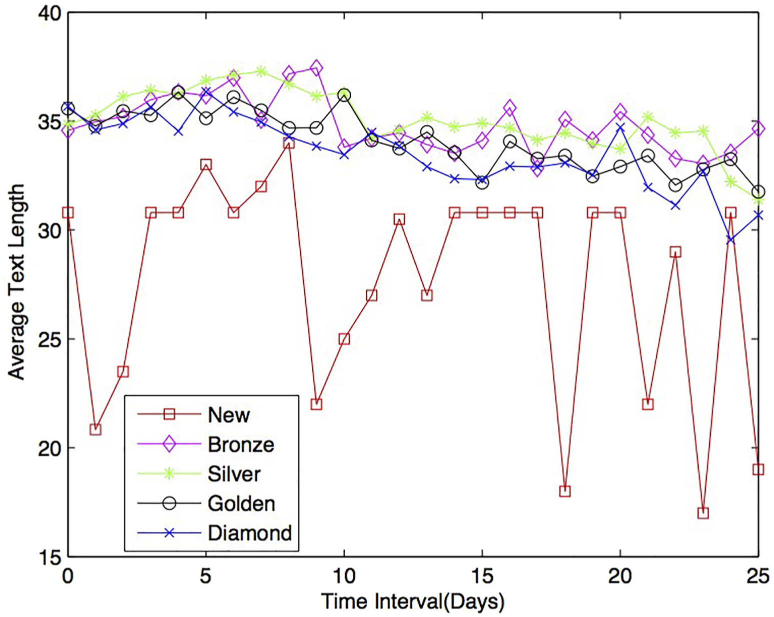

Figure 7.
Average length of review text for different membership

factor for e-commerce dealers. *log*(*Price*) also showed a negative effect such that, in the Chinese e-market, there exists some conspicuous consumption behavior in the cell phone market.

The final test results are included in Table 9:

5. Discussion

5.1 Contributions to the literature

This study explores the various incentive motivations that customers generate in their shopping experiences, and then examines the impact of these experiences on the promptness of customer reviews. In theory, this paper has two main contributions.

On the e-commerce platform, different customers often have different motivations to make reviews and different shopping experiences will also lead to different commentary drivers. It is difficult to observe the customer's motivation in commentary and published reviews, or to explore the impact of this motivation on customer commentary behavior. Therefore, this paper first finds out the commentary motivation characteristics of the user's review behavior and the characteristics of their shopping experiences. Among them, the characteristics of the user's membership level reflect the social influence motivation and the motivation of money incentives. The commentary behavior of high-level members is more susceptible to social influence drivers, while the review behavior of the low-level members is more susceptible to money incentives. Therefore, both types of members will review more promptly. The user's rating reflects the motivation for venting emotions. Users who give high scores are very satisfied with their shopping experiences and are willing to share them with others. Such users will post reviews in a more timely manner. Through these conclusions, the research on online review can be combined with the UGC data to identify the user's commentary motivation more easily and accurately, without the need to query the user through questionnaires.

Therefore, the first contribution of this research is that it links the real user commentary behavior on the e-commerce platform with the word-of-mouth communication motivation, and finds a series of behavioral feature variables that characterize the motivation. This part of the work has perfected the motivation theory of word-of-mouth communication and improved the applicability of the theory in the field of online review research.

Secondly, from the perspective of the user's shopping experience, this paper explores the various reasons that affect the promptness of the reviews in light of the user's commentary motivation, thus advancing the research in this field. The study in this paper finds that customers with low membership levels will review more quickly because of money incentives; while customers with higher membership levels will post reviews faster because of social influences. For the motivation of venting emotions, customers who are very satisfied with the experience will review faster. At the same time, we also find that when buying a higher-priced product, customers will review more quickly to "show off". In addition, experience in platform services, logistics services, product appearance, etc. will prompt customers to review faster. Those who are concerned about product features, and those who buy products for friends and family, will need more time to get relevant experience information, and will therefore make reviews slower. These conclusions include the influencing factors of commentary motivation, shopping process, customer characteristics and so on, which improve the research on the promptness of reviews from the theoretical level.

5.2 Implications for practice

On the e-commerce platform, online reviews reflect the opinions of users based on their shopping experience. At the same time, this information has a significant impact on the platform, the merchant and subsequent potential customers. The research results of this paper help to better explain the user's review behavior. The participants of the e-commerce

H	Description	Result
H1	The focus of the user experience on product features will have a positive impact on review promptness	Partially supported
H2	Positive rating has a negative impact on review promptness	Supported
H3	Membership level has a positive impact on review promptness	Supported
H4	The experienced service of e-commerce platform has a negative impact on review promptness	Supported
H5	The experienced service of logistics has a negative impact on review promptness	Supported
H6	Social effect has a negative impact on review promptness	Rejected

Table 9.
Summary of results

platform trading process can also be enlightened and improve their management. Specifically, the practical significance of this paper includes the following three aspects.

With the findings of this paper, the e-commerce platform can better identify existing reviews and provide customers with more useful information. The research in this paper finds that the differences in the promptness of customer reviews reflect the differences in customer motivation, personal characteristics and shopping experience. Customers with more timely reviews may have the following characteristics: very satisfied with the shopping experience, lower membership level, purchase of higher-priced products, and more attention to product appearance, logistics services, platform services and so on. Customers with less promptness in reviews mention the features of the product in the reviews more, and are very willing to buy products for friends and family. Platforms often require information screening for massive reviews to provide better information services to platform participants. Through the feature of review promptness, the platform can distinguish the potential information expressed by the users who reviewed from the aspects of commentary motivation and shopping experience, and therefore have a better understanding of what users think.

At the same time, in order to generate more reviews, the platform sometimes needs to remind customers to post reviews in a timely manner. Due to the relatively more prompt reviews, the platform can motivate customers to post reviews at an earlier point in time after the customer receives the goods. In order to formulate a more appropriate incentive strategy and achieve better goals, the platform should first understand the various factors that influence the customer's commentary behavior and take targeted measures. For example, for customers with lower membership levels, moderate monetary incentives can prompt them to post reviews more quickly; reminding higher-ranking customers from a social impact perspective can also prompt them to post reviews faster. In particular, when launching a new product, the platform can focus on promoting and generating posts of reviews and solving the cold start problem.

Customer reviews include reviews of products and merchants. This important feedback can help merchants better understand the user experience and improve product and service in subsequent production and service processes. When bring a new product to the market or updating an existing product, the merchant often needs to collect customer feedback in time to better understand the customer's perception of the product. At these time nodes, it is necessary to promote faster reviewing by customers and to understand the differences in perceptions of the service process by reviewing users with timely differences. For example, most of the customers who reviewed faster mentioned the aspects that were easier to experience, such as product appearance. However, for functions that require more time to experience and evaluate, reviews will be published more slowly. Merchants can first analyze the experience time of all aspects of the product, and then, in accordance with the promptness of the reviews, fully observe the user's feedback on all aspects of the product, and promptly motivate customers to review. Businesses can better identify the information they need with a better understanding of the various reasons that affect the promptness of customer reviews.

Additionally, for newly released products or new versions of products, potential customers can make better decisions with sufficient reviews. However, they should also be aware that in the past, customers need a certain amount of time to get a relatively complete experience. When new products are released, timely and strong reviews may not fully reflect the advantages and disadvantages of the products. At this time, most of the features that can be reflected from the reviews are the appearance, packaging and logistics of the products. The conclusions of this paper can also help customers to view the information more rationally and reduce the risk of decision-making.

5.3 Strengths and limitations

The main focus of this paper is on the promptness of user reviews on the e-commerce platform. The data used is crawled only from www.jd.com. Researchers who need to study the user review behavior of other e-commerce platforms or other review communities may need to conduct further analysis according to the selected research subjects.

In addition, some of the variables studied in this paper are unique. For example, the membership level strategy of other platforms or communities may be different from the research in this paper; the time of purchase and the time of the review on some platforms are not displayed at the same time, and therefore the promptness of reviews cannot be calculated.

6. Conclusions

This paper presents a methodological framework for the study of the motivations of online reviewers with particular attention paid to purchase-review promptness and reviewed contents.

First, the length of time elapsed between purchase and review was found to follow a power-law distribution, which characterizes an important number of human behaviors. Within online review behaviors, this meant that a high-frequency population of reviewers tended to publish relatively quick reviews online. This showed that the customers' reviewing behaviors on e-commerce websites might have been affected by extrinsic motivations, intrinsic motivations or both. Second, the proposed review-to-feature mapping technique was a feasible method for exploring reviewers' opinions in both massive and sparse reviews. Finally, the customers' reviewing behaviors were found to be mostly consistent with reviewers' motivations.

The analytical and experimental results gleaned from real data from a Chinese B2C website demonstrated that the consumers' reviewing behavior could provide valuable information about their motivations and concerns regarding the online shopping experience.

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