

Do reviews from friends and the crowd affect online consumer posting behaviour differently?

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Differentiating the impact between friend and crowd reviews on online consumer posting behaviour

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Abstract

User-generated reviews are valuable resources for consumers to gain information of products which has significant impact on their following decision-making. With the development of social network service, consumers are exposed to reviews coming from both friends and the crowds (non-friends). However, the impact of friends' and crowds' reviews on consumer posting behaviour has not been well differentiated. Using the online review information as well as the underlying social network from Yelp, this paper develops a multilevel mixed effect probit model to study the impact of consumer characteristics and reviews of different sources, i.e. friends or crowds, on the possibility of consumer further engaging in posting behaviour. Despite the common perception that the volume, valance and variance of reviews significantly impact the possibility of following posting behaviour, we show that such influence majorly comes from the friend reviews. The volume of friend reviews has much stronger impact on the target user's posting behaviour than that of the crowds. The valance and variance of the crowd reviews show no significant influence when ignoring the friend reviews, but negative influence when considering it. The friend reviews and crowd reviews are further divided as positive and negative ones, and only the positive friend reviews and negative crowd review are found significantly enhancing the posting possibility.

Keywords: Online review, Posting behaviour, Word-of-Mouth, Social networks, Social influence

1. Introduction

Thanks to the advent of information technology, online user-generated content systems have been widely developed, which enable users to post reviews, exchange opinions, and share experiences in real time (Cha et al., 2007; Dhar and Chang, 2009). In particular, such system has become an essential channel where potential consumers get information of products by examining previous buyers' reviews (Ye et al., 2011; Goes et al., 2014).

The online reviews, recognised as electronic Word-of-Mouth (eWOM) (Hennig-Thurau et al., 2004; Chu and Kim, 2011), are found to have significant impact on the following consumer behaviour (Chevalier and Mayzlin, 2006; Schlosser, 2005). Those reviews are also appreciated by companies as valuable marketing resources (Jung et al., 2013; Chen et al., 2011). Given the development of Web 2.0, consumers in these online systems are not only the receivers but also the creators of online information, and their engagement consequently has become increasingly crucial for competitiveness (Brodie et al., 2013) and marketing strategies (Pralhad and Ramaswamy, 2013) of e-commerce websites. Therefore, to study how existing online reviews influence future user engagement to the online system is of importance from both theoretical and practical perspectives.

It is widely acknowledged that, many dimensions, such as volume, valance and variance of the online reviews can notably enhance the possibility for consumers to in turn engage in it (Punj, 2013; Guo and Zhou, 2016). For instance, users are more likely to post reviews to the

movies that have high variance of prior ratings (Lee et al., 2015). Product characteristics and consumer traits also have significant impact on the eWOM communications (Berger and Milkman, 2012; Cheema and Kaikati, 2010). Berger and Milkman (2012) found that some internal states of consumers such as emotions induced by online content could influence the possibility of their engagement in the eWOM communications. Additionally, others' reviews may also influence the target consumer's post-consumption evaluation (Schlosser, 2005), which is usually referred as the tendency of confirming others' actions. For example, a reviewer may adjust his/her rating upward for a movie if the prior ratings posted by others are high (Moe and Schweidel, 2012).

To make eWOM more appealing, social network services are available in a wide range of online systems. Consequently, consumers can access online reviews coming from both the crowds (non-friends) and their friends. Due to the frequent interactions, the eWOM from friends has strong influence over one's engagement in posting behaviour (Centola, 2010; Crandall et al., 2008; Dellarocas et al., 2006; Aral and Walker, 2011). Actually, such influence on one's behaviour from social ties has long been reported in social science (Brown and Reingen, 1987; Steffes and Burgee, 2009; Kawachi and Berkman, 2001; Wang and Chang, 2013) and is normally recognised as the social contagion phenomenon (Aral and Walker, 2011; Aral et al., 2009).

Both friends and the crowds have been found influential over consumer engagement in WOM in the literature. The crowds have much larger population than that of a consumer's friend circle, which implies that the reviews and opinions would be of much greater diversity

and richness. Therefore, the reviews from the crowds may provide much more information for consumers to make purchase decisions and further engage in post-purchase discussions. However, on the other hand, friends normally have closer relationships and similar preference with the target consumer resulting in trust and frequent interactions (McPherson et al., 2001). Thus, consumers are more likely to consider friends' opinions and suggestions than others'. In this paper, we adopt a social network perspective to examine, in an online context, how friend reviews and crowd reviews differently influence the subsequent consumers' posting behaviour. This study may deepen our understanding of the motivations of consumers' engagement in the eWOM communications by exploring the role of trust and homophily in the social interactions among consumers. The findings may shed insights on the approaches for online marketing through social networks, and better design of the user-generated content systems.

Although some efforts of differentiating friends and the crowds (Lee et al., 2015; Muchnik et al., 2013) have been made, they only focus on the rating behaviour. Do friend reviews and crowd reviews differently impact the posting possibility, which is a prior stage to rating, is still an open question. Applying a large scale of review data from Yelp.com, the present paper aims to differentiate and compare the impact of friends' and the crowds' reviews on the possibility of consumers engaging in the activity of posting reviews from three aspects of reviews: volume, valance and variance. We develop a multilevel mixed effect probit model to examine the possibility of posting behaviour, in relation to review information and consumer characteristics. Friend reviews and crowd reviews are found with different impact on posting behaviour. The volume of friend reviews shows stronger impact on the possibility of posting behaviour than

that of the crowd reviews. The valance and variance of crowd reviews show no significant influence when ignoring friend reviews, but have negative influence when considering them. In addition, we study the impact of positive and negative WOM of friends and crowds. The results show that the volume of positive friend reviews and negative crowd reviews have significant influence on the subsequent engagement on WOM communications.

The paper is organised as follows. Section 2 introduces the relevant literature of eWOM, and section 3 develops hypotheses. The data collection and model are presented in section 4. The results and discussions are reported in the section 5 and 6, respectively.

2. Related work

2.1. Word-of-Mouth Theory

Word-of-Mouth (WOM) is defined as informal communication between private parties concerning evaluations of goods and services (Anderson, 1998). An electronic version of WOM has got increasing attentions as the Internet is transforming the way we access to information and communicate with each other.

In the early stage of WOM study, the motivations of consumers to engage in the post-consumption WOM behaviour has been widely discussed. Dichter (1966) identified four key motivations that drive individuals to engage in it: first, perceived product involvement, second, self-involvement such as gratification of emotional needs from the product, third, other involvement like a need to give something to the person receiving the WOM transmission, and last, message involvement like the way to present the product in the medias. Sundaram et al. (1998) found that the desire of consumers for altruism, product involvement and self-

enhancement are the main factors leading to positive WOM, while negative WOM normally due to anxiety reduction and vengeance purpose. Hennig-Thurau et al. (2004) concluded that social benefits, economic incentives, concern for others and extraversion are the main motivations for consumer to participate in WOM on the Internet. The intentions to engage in positive or negative eWOM are associated with different antecedents (Fu et al., 2015; Brown et al., 2005). Fu et al. (2015) found that consumers who have a favourable attitude towards the eWOM communications intend to post positive online reviews, whereas negative eWOM are more driven by social pressure.

2.2. Impact of online reviews on consumer behaviour

Online reviews, as one of the most typical versions of eWOM, significantly influence pre-consumption decision-making (Godes and Mayzlin, 2004; Duan et al., 2008) and post-consumption evaluations (Dellarocas et al., 2006). According to the surveys (Staff, 2007a, b), 82% of the consumers believe that their decisions of buying products are directly influenced by online reviews and over 75% of them will consider the recommendations from buyers who have experience of this product. A lot of research have studied the association between how a product such as a movie or a book has been rated by consumers and its subsequent sales (Godes and Mayzlin, 2004; Chevalier and Mayzlin, 2006; Dellarocas et al., 2004; Duan et al., 2008). Chevalier and Mayzlin (2006) reported that the consumer reviews have a positive impact on the subsequent book sales in Amazon.com and Li and Hitt (2008) found similar results for the website of Barnesand-Noble.com.

Three aspects of online reviews, namely volume, valance and variance (Dellarocas et al., 2006), have been widely addressed. Volume, which is measured by the number of reviews posted by consumers, is the popularity of the item. The more popular a product is, the more likely it would be further purchased and commented by others. Liu (2006) and Duan et al. (2008) found that the volume of reviews has significant positive impact on the box office sales of movies. Valance, which is normally quantified by the average rating, can largely represent the quality of a product. Dellarocas et al. (2005) showed that the valance of online ratings posted during a movie's opening weekend is the most important predictor of its revenue trajectory in the subsequent weeks. Similarly, Chintagunta et al. (2010) found that the valance of pre-release advertising is the main driver of box office performance. Studies also addressed the relation between consumer posting behaviour and the rating environment they are exposed to in term of the volume and valance of ratings. Moe and Schweidel (2012) found that a consumer is more inclined to share his experience when the the volume and valance of previous ratings are high. Variance, which is measured by statistical variance measures as well as other dispersion methods such as entropy, normally represents the fluctuation of user opinion. Clemons et al. (2006) found that the sales of beer grow faster for the brands with higher variance of ratings. Godes and Mayzlin (2004) found that the variance of opinions about weekly TV shows across the Internet communities positively related to the evolution of viewership of these shows. Sun (2012) investigated the interaction effect between the valance and variance of ratings and found that a higher variance of one book on Amazon could increase

its sales if and only if the average rating is lower than aspiration level (approximately 4.1 out of 5 as they claimed).

In addition to the "3Vs" of online reviews, many studies have argued that reviewer characteristics also play significant roles on product sales and consumer behaviour (Zhu and Zhang, 2010; Hu et al., 2008; Forman et al., 2008). When accessing to online reviews, consumers normally pay attention to both the review information and other contextual information about the reviewer such as the reviewer credibility, reputation and exposure (Hu et al., 2008). Forman et al. (2008) suggested that reviewer disclosure of identity description information is significantly and positively associated with both perceived helpfulness of reviews and product sales.

2.3. Friend impact versus crowd impact on consumer posting behaviour

Individuals are always engage in group life and the interactions between friends are more frequent than that of crowds. Thus, it is very common that people behave similar to their friends (Lewis et al., 2012; Ji et al., 2015). Yet, different friends may have different impact over a specific consumer. The strength of social ties, which measures the closeness of the relationship among people (Granovetter, 1973), has been found to have impact on the process of decision-making (Steffes and Burgee, 2009; Wang and Chang, 2013). The effect of strong ties (friends) and weak ties (acquaintances) on consumer behaviour are different in some situations. Brown and Reingen (1987) found that consumers generally perceived friends to be more influential than acquaintances in their decision-making. Steffes and Burgee (2009) investigated how social ties relate to eWOM among college students and found that the source of information from

different tie strength friends differently affects their decisions. While those studies have drawn the link between social tie and consumer behaviour, they only consider the friends circle of the target consumer without the consideration of crowds who may have impact on his behaviours.

As most of reviews a user access to are very likely to be posted by strangers who have no social ties with him/her, it is necessary to consider friends and crowds as different sources of information. It has recently caught some attentions to study the different impact of the two information sources on consumer behaviour. Lee et al. (2015) investigated the different impact of friends' and crowds' ratings of products on a subsequent user's rating for a movie. They found that friends' ratings always induce herding behaviour, but the presence of social networking reduces the the likelihood of herding by crowds. Muchnik et al. (2013) found that individuals' rating behaviour differ from prior ratings and the difference depends largely on the source of prior ratings, i.e. friends or enemies. Though such different impact on rating behaviour has been explored, rating is only one of many stages of the engagement activity to eWOM. Whether to post reviews or not, being the prior stage of deciding a grade, is a more significant subject for the study of understanding consumer behaviour. And the issue that how friend review and crowd review differently impact on it should be addressed.

3. Hypotheses Development

Inspired by the literature (Zhu and Zhang, 2010; Moe and Schweidel, 2012), we model the consumption process as shown in Fig. 1. Before making a consumption decision, users firstly gather information about the product as well as previous reviews posted by other consumers. The target consumer's characteristics, product information as well as the review

information posted by either his/her friends or the crowds will jointly influence his/her decision on whether to consume this product. Once consumed, consumers will decide either to be a poster to share their experience such as a numerical rating, text review, and even some photos, or to be a “lurker” who only read reviews but do not post.

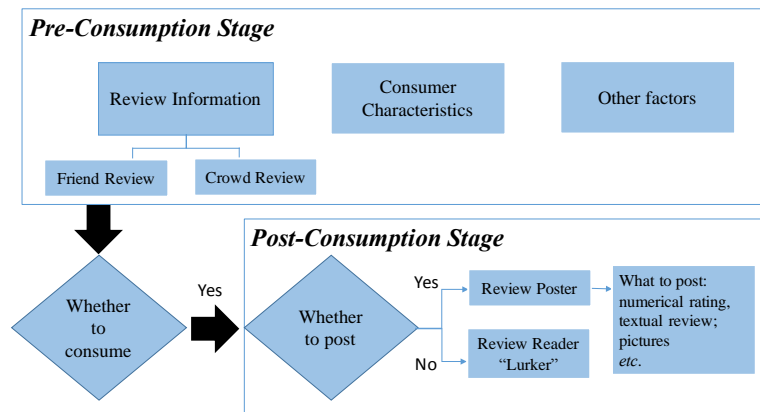


Fig. 1: Process of online consumption and post-consumption evaluation

According to such consumption process, this paper aims to firstly identify the influential factors in the pre-consumption stage for the possibility of a consumer to post a review, and secondly detect if the impact of friend reviews and crowd reviews are different for consumer posting behaviour. To do so, a number of hypothesises are developed as shown in Fig. 2.

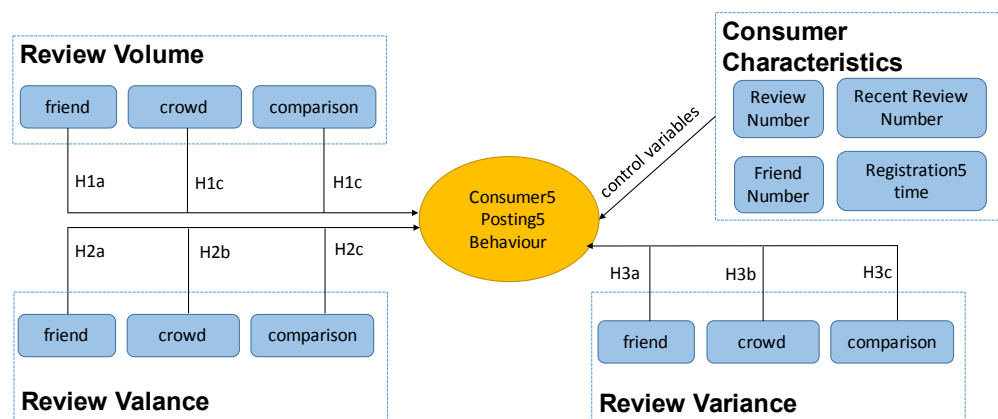


Fig. 2: Research Model

3.1. Review volume

Consumers tend to select products with more reviews. Firstly, popular products get more attentions because most of consumers are aware of them and a large volume would make the reviews more objective and trustworthy. Chen et al. (2004) showed that the average rating converges to the true quality with the increase of the review number. Therefore, reviews of popular products can more accurately reflect the true quality. Furthermore, consumers are more likely to access the information of popular products because they are exposed to these reviews more frequently. It has been suggested that a favourable feeling can be created after sufficient exposure, which can be interpreted as an exposure effect (Bornstein, 1989; Zajonc, 1980). As popular products are reviewed more frequently and consumers are exposed to them repeatedly, the exposure effect would make consumers more likely to choose them and further engage in the discussions about them in turn. Accordingly, we hypothesis consumer posting behaviour is positively related to the volume of both friend and crowd as,

Hypothesis 1a (H1a): The review volume of a product from the crowds positively influences the possibility of subsequent consumer engagement in posting behaviour.

Hypothesis 1b (H1b): The review volume of a product from a target consumer's friends positively influences the possibility of his/her engagement in posting behaviour.

Friends usually play a more significant role in several aspects of consumer purchase selection and posting behaviours (Pan et al., 2017; Lee et al., 2015). Friends normally have similar tastes and preferences of product selection (McPherson et al., 2001) as well as more frequent interactions. This may facilitate consumers to select the products that are popular

among friends and join them to engage in the post-consumption WOM communications. It has been suggested that review information posted by friends is perceived as more credible, leading to significant influence over individual's decision-making (Granovetter, 1973). A tendency toward transitivity is exhibited in friends' social network according to Granovetter (1973), which means if person A is friend to person B and person C, there is a high probability that B and C become friends. Clark and Loheac (2007) proved this tendency to be also existed in brand preference for consumer who belongs to the same friend circle. In addition, our recent study (Pan et al., 2017) developed a model describing whether consumers follow their friends or the crowds to make selections, and found that 75% of the selection behaviour are driven by the friend opinions. Therefore, the following hypothesis is developed:

Hypothesis 1c (H1c): Review volume of a target consumer's friends are more influential on his/her posting behaviour than that of the crowds.

3.2. Review valance

When users make consumption decisions, a high valance, which is the average rating can largely enhance the chance of a product to be selected. The highly-rated products are consequently more likely to be commented. Ma et al. (2013) reported that the average of previous ratings can serve as a signal to help the following consumers to form the first impression about the product, and therefore positively impact the subsequent consumer decision-making. Many studies have shown a positive link between the rating of products and sales (Godes and Mayzlin, 2004; Chevalier and Mayzlin, 2006; Clemons et al., 2006). They believed that the review valance could reflect the quality of items and people rely more on

positive cues (high valance) than negative ones. Doh and Hwang (2009) showed that reviews with high stars have positive significant effect on purchase intention. Gershoff et al. (2003) suggested that positive reviews have a stronger impact than negative one. Thus, in this paper we hypothesis that subsequent consumer may pay more attentions to those reviews with high valance, that,

Hypothesis 2a (H2a): The average of ratings posted by the crowds positively influences the possibility of subsequent consumer engagement in posting behaviour.

Hypothesis 2b (H2b): The average of ratings posted by a target consumer's friends positively influences the possibility of his/her subsequent engagement in posting behaviour.

However, some studies argue that the review valance may not reflect the true quality of products (Li and Hitt, 2008) for two reasons. One is due to "forum manipulation" that firms employ paid reviewers to create high ratings. The other is that ratings may represent a mix of objective product quality and subjective assessments of value based on consumer fit. Therefore, it is believed that the ratings may be biased. For example, the early ratings of a start-up business may be very high, while it is possible that the firm created some fake reviews to appeal consumers.

The fact that the crowd ratings may overestimate the product quality, makes friend reviews more credible to consumers. Driving by the intuition that "if I like that person I might also be interested in his content", users' friends normally provide better recommendations than others (Sinha et al., 2001). Thus, consumers are more likely to trust the average rating of friend

review, rather than that of the crowds. Social networks are communities that can be sustained by a sense of participation (Zhang et al., 2011). A well established community makes people feel useful and a sense of belonging (Zadeh et al., 2010). Therefore, a forward loop may exist in the community that consumers have tendency to join friend discussions. We therefore hypothesize the following,

Hypothesis 2c (H2c): Review valence of a target consumer's friends are more influential on his/her posting behaviour than that of the crowds.

3.3. Review variance

The variance of ratings is a common method to capture the heterogeneity of consumer opinions. From a managerial perspective, variance is also an easy way to monitor the consumer preferences and predict potential purchase decisions. Normally, a low variance may suggest the product to fit a broad range of interests, while a high variance associated to a niche product suiting only a small group of consumers' interests. Additionally, it has been found that consumers tend to post extreme ratings when there is a big gap between their perceived quality and expectation (Anderson, 1973). The distribution of product rating thus has a right skewed U-shape (McGlohon et al., 2010; Anderson, 1998), which means consumers who are extremely satisfied or unsatisfied are more likely to post an opinion.

Discordant opinions can be found in literature. Evidences have been found that inconsistent ratings have negative impacts on the subsequent demand or sales due to the fact that high variance may lead to high risk of getting bad experiences (Muchnik et al., 2013). On contrast, it has also been argued that high variance in rating may trigger curiosity leading to

higher demand and more discussions (Clemons et al., 2006; Sun, 2012). The discordant findings are probably related to the product types, i.e. searching good or experience good (Mudambi and Schuff, 2010). The quality of experience goods can hardly be gained before consumer actually experience (purchase) them, which makes online rating of prior buyers to be a quick approach. For example, Ye et al. (2011) indicates the high variance of prior ratings can significantly decrease the sales of hotel rooms which are typical experience goods. On the other hand, high variance product reviews are found to facilitate the possibility of purchase of MP3 players (Park and Park, 2013) which subject to search goods. As the target products to be studied in the present paper are experience good, including restaurants, hotels etc., we accordingly propose the following hypothesis:

Hypothesis 3a (H3a): The variance of ratings posted by the crowds negatively influences the possibility of subsequent consumer engagement in posting behaviour.

Most of prior online review studies have focused on the impact of variance of all ratings, while little known about how friend rating distribution could matter. Diffusion of innovation theory posits that new ideas, practices and objects become known and spread quickly within communities (Gatignon and Robertson, 1985). Individuals within a friendship network act as WOM channels and raw models to inspire others to imitate their behaviour leading to consumption experience (Flynn and Goldsmith, 1999). However, the long developed spiral of silence theory (Noelle-Neumann, 1974) of social science has suggested that open deliberation may be impeded when friends' opinions disagree from each other in a social discussion such as political election. Hampton et al. (2017) found that the disagreement between friends

reduces the willingness of users to in a social network to join a conversation. Considering that reviewing online products is also a social discussion process, we accordingly develop following hypotheses:

Hypothesis 3b (H3b): The variance of ratings posted by a target consumer's friends negatively influences the possibility of his/her subsequent engagement in posting behaviour.

Hypothesis 3c (H3c): Review variance of a target consumer's friends are more influential on his/her posting behaviour than that of the crowds.

4. Data Collection and Model Specification

4.1. Data collection

To analyse the impact of friend reviews and crowd reviews as well as the consumer characteristics on the possibility of a consumer to engage in the eWOM, we apply a large scale of empirical review data from a user-generated content system, Yelp. In Yelp, a user can access to the information of various businesses such as restaurants, hotels etc. as shown in Fig. 3. Notably, Yelp also provides social network service, which allows users to connect their friends in the system. A user can either go to the homepage of a business to go through its basic information (Fig. 3 a) and all reviews (Fig. 3 b), or check his/her friends' recent reviews as a timeline displaying on his/her homepage (Fig. 3 d). As a consequence, the reviews of both friends and the crowds may potentially influence a user's consumption behaviour and his/her evaluations of post-consumption. According to the consumption process shown in Fig. 1, the posting of reviews follows the consuming behaviour. But in Yelp system it is impossible to

know for sure that whether each reviewer has consumed the product (business), because Yelp is merely a platform for sharing experiences and opinions which does not sell anything. However, the major purpose of posting reviews, especially in Yelp where most products are restaurants, is to share experience. Though there is a possibility that the reviewer could make up experiences without really experiencing, we believe such possibility is reasonably slim. Accordingly, we assume that all the reviews are posted after consumption. Such settings make the Yelp system an ideal scenario for us to explore the different impact of friends' and the crowds' reviews.

The dataset we apply in this paper is published by Yelp. This dataset consists of 1569264 reviews posted by 366715 users on 61184 businesses in a time period from the year of 2005 to 2015. Especially, the explicit relationship, i.e. the social network, among these users is known. Therefore, for a target user, we can identify whether a review was posted by the crowds or his/her friends. To avoid the sparsity problem of the data set (Pan and Zhang, 2011), here we prepare the data for analysis as following:

- 1) While more than 70% of the reviews in the dataset were posted after 2010, we only focus on the time period of 50 weeks from 1st August, 2014 to 15th July, 2015, when the posting behaviour is flourishing.

- 2) We target at only the businesses which are located in the Phoenix city and have at least 100 reviews. Accordingly, 523 businesses are selected and as shown in Table 1, most of which are restaurants.

3) For these selected businesses, the reviews came from more than ten thousand consumers. We randomly sample 1000 consumers from them who have at least ten friends, so that we can explore the different impact of friends' and the crowds' reviews on their posting behaviour.

Table 1: Description of data

Data level	Numbers	Description
Users	1000	The number of users sampled from the the Yelp dataset.
Business	523	The number of businesses sampled from the Yelp dataset.
		Category of Business
	414	Restaurant
	15	Arts and Entertainment e.g Museum
	14	Hotel
	7	Public Services e.g. Library, Delivery
	6	Shopping Centre
	5	Active life e.g. Zoo, Parking
	4	Home Services e.g. Key, Heat
	4	Hair or nail Salon
Duration Time	50	Number of weeks in the sampled data

4) We regard each week as a time step t , and assume each of the 1000 consumers can possibly post a review on each of the 523 businesses in each week. As a consequence, there are $1000 \times 523 \times 50 = 2.615 \times 10^7$ data records for the regression analysis, and each record describes the posting behaviour of consumer u to the business b at the time step t .

5) The dependent variable is a dummy variable. For each data record, if the user u posted a review to business b at the time t , the corresponding value of the dependent variable would be 1, and 0 otherwise.

6) The independent variables correspond to the developed hypotheses. The volume of reviews, i.e. the popularity is measured by the number of all reviews of the business b before

week t . Counting the number of reviews posted by non-friends (the crowds) and friends, we then have the review volume among the crowds CP_{ubt} , and the review volume among friends FP_{ubt} . Each review is associated with a numerical integral rating ranging from 1 to 5. The valance is measured by the average rating of reviews posted by the crowds and friends before week t respectively, i.e. average rating of the crowd review CR_{ubt} and average rating of friend review FR_{ubt} . The variance CVR_{ubt} and FVR_{ubt} are the statistical variances of reviews on business b before week t posted by the crowds and consumer u 's friends, respectively. Note that the calculation of the reviews, i.e. the volume, valance and variance, is based on the whole data set, with 366715 users rather than the sampled 1000 users. Drawing from the literature (Lee et al., 2015; Moe and Schweidel, 2012), we consider four control variables. The number of historical reviews NOR_{ut} and the review number in the recent week $NORC_{ut}$ are extracted from the whole data set until the week t , not limited in the sampled 523 businesses. The number of friends NOF_u in the Yelp data is static, i.e. we only know the number of a user u 's friends at the end of the data, with no information of the exact time of them becoming friends. The age of the user T_{ut} is the number of weeks since his/her registration week RT_u until the week t , i.e. $T_{ut} = t - RT_u$.

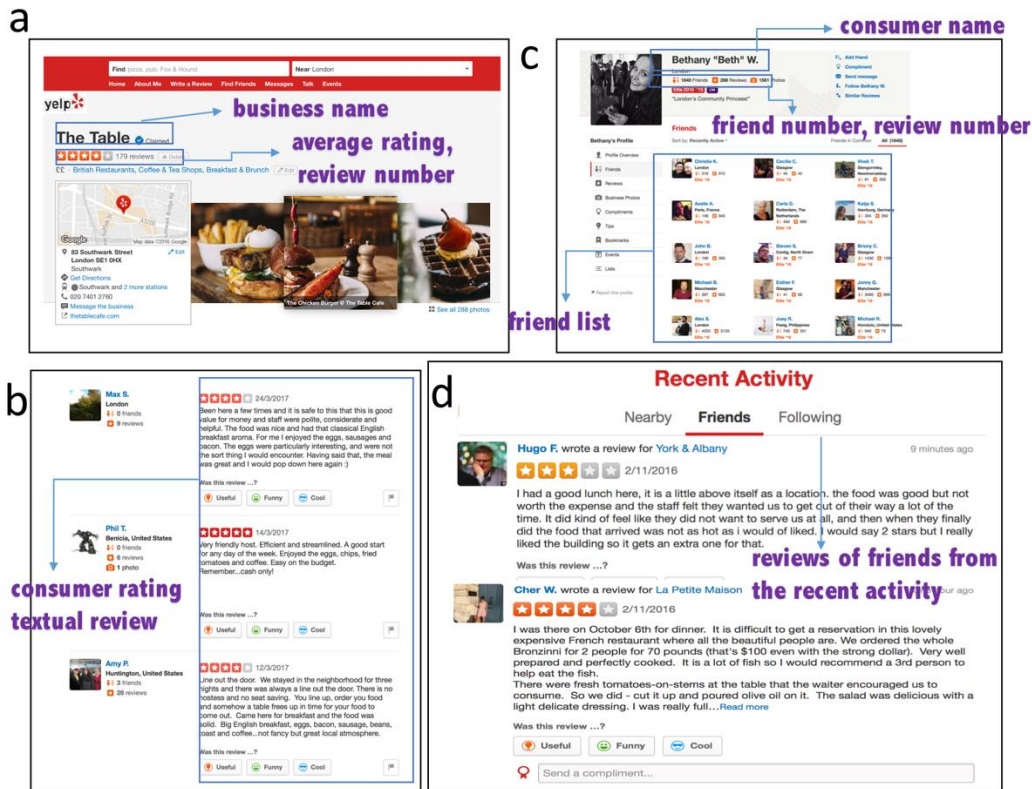


Fig. 3: (Colour online) (a) Homepage of a business in Yelp. (b) Reviews of the business shown in Fig.3(a). (c) A user homepage in Yelp. (d) Recent friends' reviews.

In summary, the data for regression analysis is a dense sample including 1000 users and 523 businesses in a time period of 50 weeks, but the independent variables including consumer characteristics and the 3V of friend and crowd review are calculated or extracted from the whole data set with a temporal manner. Some descriptions on the independent variables can be found in Table 2.

Note that, the regression data prepared according to the described method is based on the consumers who have at least ten friends in Yelp. To address the impact of friend review, we also extract another regression data as control following the above steps but in step 3), sample 1000 consumers who have no friends in the system.

Table 2: Data Description Statistics

Dimension	Variables	Description	Min	Max	Mean
User characteristic	NOR_{ut}	Number of reviews submitted by user u until the week t	0	447	14.89
	$NORC_{ut}$	Number of reviews submitted by user u at the week $t-1$	0	48	0.44
	NOF_u	Number of friends of user u	10	1360	43.41
	T_{ut}	Weeks since user u registered	5	149	83.29
Crowd Review	CP_{ubt}	Number of reviews of business b in the whole system before week t	0	1186	150.47
	$PosCP_{ubt}$	Positive number of crowd review of business b before week t	0	832	148
	$NegCP_{ubt}$	Negative number of crowd review of business b before week t	0	354	27.78
	CR_{ubt}	Average rating of business b in the whole system before week t	1.00	5.00	3.86
Friend Review	CVR_{ubt}	Variance of all ratings submitted until the week t	0	1.88	1.06
	FP_{ubt}	Number of user u 's friends who have commented business b before week t	0	104	0.45
	$PosFP_{ubt}$	Positive number of user u 's friends who have commented business b before week t	0	64	1.82
	$NegFP_{ubt}$	Negative number of user u 's friends who have commented business b before week t	0	28	0.39
	FR_{ubt}	Average rating of user u 's friends who have commented business b before week t	1.00	5	3.95
	FVR_{ubt}	Variance of all ratings of business b submitted by user u 's friends before the week t	0	2	0.24

4.2. Model specification

Our dataset has multilevel structure: consumer level and business level. Therefore, user or business heterogeneity can be appropriately controlled by an individual's or one business's observed characteristics. In addition, one week as a time stamp for posting reviews enables us to control some unexplainable change across time. Based on the previous studies (Moe and Schweidel, 2012; Ying et al., 2006; Lee et al., 2015), here we develop a multilevel mixed effect probit model to describe the possibility of posting behaviour, which separates the friend reviews and crowd reviews and also consider consumer characteristics and a random effect to

reflect the varying baseline tendency of posters. We assume a consumer u would post a review for a business b at time t if

$$U_{ubt}^* = \delta_{u0} + \beta \cdot V_{ubt} + \mu_{ubt} > 0, \quad (1)$$

where V_{ubt} is the vector consisting of influential factors which may include the mentioned three aspects: consumer characteristics $X_{ut} = \{NOF_u, NOR_{ut}, NORC_{ut}, T_{ut}\}$, crowd review information $C_{ubt} = \{CP_{ubt}, CR_{ubt}, CVR_{ubt}\}$, and friend review information $F_{ubt} = \{FP_{ubt}, FR_{ubt}, FVR_{ubt}\}$. The term μ_{ubt} is an idiosyncratic error and the term δ_{u0} represents the varying baseline tendencies for individuals to submit a review. The standard deviation of δ_{u0} is σ_{δ_0} .

To address and compare the impact of friend reviews and crowd reviews on consumer posting behaviour, we develop three models to analyse the data. As a control, model 1 specifically studies a group of consumers who have no friends at all, and thus only considers the consumer characteristics X_{ut} and crowds' review information C_{ubt} . Accordingly, the possibility of consumer u to post a review to business b at week t gives by the probit model:

$$\text{Model1: } \Pr(z_{ubt} = 1) = \Phi(\delta_{u0} + \delta_{1:4}X_{ut} + \omega_{1:3}C_{ubt}), \quad (2)$$

where $\Phi(\cdot)$ denotes the standard normal cumulative distribution function and $z_{ubt} = 1$ indicates that there is a review and vice versa. Since those consumers have no friends, all the possible impacts come from either themselves or the crowds. On contrast, we also analyse the behaviours of consumers with at least ten friends. In respect to model 1, we develop model 2 to also consider only the consumer characteristics X_{ut} and crowds' review information C_{ubt} , and therefore we have,

$$\text{Model2: } \Pr(z_{ubt} = 1) = \Phi(\delta_{u0} + \delta_{1:4}X_{ut} + \omega_{1:3}C_{ubt}), \quad (3)$$

Note that, the expressions for both model 1 and model 2 are the same, but are applied to different data sets. Model 1 studies consumers with no friends, while model 2 studies consumers with at least ten friends. At last, we apply all the possible factors to study the impact of friends' and crowds' reviews on consumer posting behaviour in model 3 by using the data in which users have at least ten friends, which reads,

$$\text{Model3: } \Pr(z_{ubt} = 1) = \Phi(\delta_{u0} + \delta_{1:4}X_{ut} + \omega_{1:3}C_{ubt} + \gamma_{1:3}F_{ubt}), \quad (4)$$

5. Results

We use the three multilevel mixed effect probit models to analyse the Yelp data and the results are shown in Table 3. To summarise, Model 1 analyses the users with no friends and thus the possibility of posting is assumed to be influenced only by the consumer characteristics and crowd reviews. On the other hand, both Model 2 and Model 3 analyse the users with at least ten friends. However, model 2 does not consider the influence of friend reviews while model 3 does. Note that, we normalise each variable using the min-max normalisation, and the estimated coefficients are therefore comparable to each other.

Table 3: Estimates of consumer characteristics, friends' and crowds' impact on posting behaviour

Variables	Model 1		Model 2		Model 3	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
δ_0	-0.449	10.929	-14.528	9.757	-3.551***	0.168
δ_1 NOR_{ut}	0.640**	0.252	0.515**	0.181	0.391*	0.183
δ_2 $NORC_{ut}$	3.840***	0.155	4.589***	0.136	4.609***	0.137
δ_3 NOF_u			0.366	0.349	-0.861*	0.383
δ_4 T_{ut}	0.271	0.21	-0.350***	0.093	-0.299**	0.094
					(Crowd)	
ω_1 CP_{ubt}	0.951***	0.074	0.612***	0.054	0.326***	0.064
ω_2 CR_{ubt}	20.56	43.72	-31.31	30.02	-0.312*	0.064
ω_3 CVR_{ubt}	-9.458	20.611	15.82	15	-0.784***	0.162

	<i>(Friend)</i>					
γ_1 FP_{ubt}					2.035***	0.271
γ_2 FR_{ubt}					0.264***	0.064
γ_3 FVR_{ubt}					0.229***	0.057
Variation of baseline tendency						
$\sigma_{\delta_0}^2$	0.141	0.031	0.21	0.025	0.21	0.025
Log-Likelihood		-3704		-7855		-7797
Wald chi2		776.7		1308		1394
Prob>chi2		0		0		0

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5.1. Review volume

For the crowd review, the volume CP_{ubt} is shown to be positively ($\omega_1 > 0$) influencing the consumer posting possibility, and the influence is significant in all three models. Thus, H1a is supported. Such result suggests a “rich get richer” effect that the businesses with a lot of reviews (high volume) tend to get more reviews. Similarly, the volume of friend review, FP_{ubt} has positive impact as well ($\gamma_1 > 0$) in model 3. H1b is supported. Though the volume of reviews has been found significant to explain the possibility of consumers’ posting behaviour (Dellarocas et al., 2006; Liu, 2006; Duan et al., 2008), the results in the present paper show different effect between the friends and the crowds. While the businesses that have been widely reviewed by either non-friends (the crowds) or friends tend to be further reviewed by the target consumer, the volume of friend review is much more influential than that of the crowd review ($\gamma_1 = 2.035$, $\omega_1 = 0.326$). The result supports H1c. As we discussed in section 3.1, a large volume of the crowd review may suggest that the business is of common interest for most of consumers, while the volume of friend review can indicate the interest of the target consumer’s local social group. Since friends normally have similar interests, tastes and so on (Ji et al., 2015; Pan et al., 2017; Leskovec et al., 2007), a consumer is more likely to select these businesses of

his/her friends' interests (high volume of friend reviews), rather than those of common interests (high volume of crowd reviews). A higher chance of getting consumed will lead to higher possibility of being reviewed. In addition, when deciding whether to post a review, a consumer may also want to behave similarly to his/her friends due to the desire of maintaining the friendship and finding common experience with friends (Schieman and Van Gundy, 2000).

5.2. Review valance

Previous studies hold different opinions towards the impact of review valance, as we presented in section 3.2. Our results regarding review valance may largely supplement the existing theories. Firstly, the valance CR_{ubt} is not significant for Model 1 and 2, which shows differences from previous studies (Godes and Mayzlin, 2004; Chintagunta et al., 2010). The reason may lie in the fact that, these studies did not distinguish the friends from the crowds and thus the valance reviews are contributed by both friends and non-friends. In the present study, on the other hand, the crowds do not include the target consumer's friends. Secondly, in our main model, the valance of crowd review is significant and negatively ($\omega_2 < 0$) influencing the possibility of consumer posting. While friends highly evaluating the business enhances the possibility for the target consumer to post ($\gamma_2 > 0$). That means consumer would like to select businesses with high average stars from friends, other than from crowds. Therefore, H2b is supported but H2a is not. The effect of the valance of crowd review is slightly stronger than that of the friends ($\gamma_2 = 0.264$ less than $|\omega_2| = 0.312$). H3c is not supported.

5.3. Review variance

Review variance represents how different consumers evaluate the same product. The variance of the crowd reviews, CVR_{ubt} , is shown to be negatively influencing consumers'

posting possibility, confirming our hypothesis H3a. However, the variance of friend reviews, FVR_{ubt} , shows positive significance ($\gamma_3 > 0$) influencing the posting possibility. The result suggests that the variance of crowd review has stronger impact on posting behaviour than that of the friends ($\gamma_3 = 0.229$ less than $|\omega_3| = 0.784$). Though the diversity of friend opinions to some extent promote more discussions, such effect may be set back by the risk of getting bad experiences i.e. high variance of crowd reviews. Consumers prefer to choose those businesses that others have consensus in their quality. Accordingly, the H3a is supported, while H3b and H3c are not.

5.4. Consumer characteristics

The consumer characteristics being control variables in this paper are shown by the results to be significantly influencing the possibility of users engaging in the eWOM. Both the number of reviews and the recent number of reviews significantly and positively ($\delta_1 > 0$, $\delta_2 > 0$) enhance the posting possibility, and thus the H1 and H2 are supported by all the three models. In particular, a user's recent activities are much more determinative than his/her historical activities ($\delta_2 > \delta_1$). The number of friends, on the other hand, is significant in only the Model 3. However, the results suggest that the number of friends is negatively ($\delta_3 < 0$) correlated with the posting possibility and thus the H3 is not supported. Such finding is different from previous studies (Lee et al., 2015), and it may originate from two possible reasons. Firstly, the number of friends, as has been discussed in section 4.1, is a static number collected at the end of the data, while the regression analysis considers a dynamic process, i.e., uses weeks as timestamp. Secondly, Model 3 considers the influence of the friend reviews, and the number

of friends may be correlated with these variables. The age of user, which is measured by the weeks since the user registered to the system, is also found negatively ($\delta_4 < 0$) influencing the posting possibility, but only statistically significant in Model 2 and 3. In other words, the users tend to post reviews in the early stage after registration, and may become less active after a while.

5.5. Types of WOM

To further discuss the different impact of friend and crowd review, we also study the impact of types (positive or negative) of WOM on consumer posting behaviour. The type of WOM is measured by the rating that we regard reviews with ratings higher than three as positive, and these less than three as negative. In particular, we also differentiate the impact the number of positive and negative friend and crowd review on posting behaviour to supplement the results for the different impact between friends and the crowds. Accordingly, four variables are derived: *PosCP* (number of positive crowd reviews), *NegCP* (number of negative crowd reviews), *PosFP* (number of positive friend reviews) and *NegFP* (number of negative friend reviews).

Past research hold different opinions toward the role of positive and negative WOM. Some (East et al., 2008; Goldenberg et al., 2007) suggest positive WOM can make subsequent consumer more positive on the advices based on satisfactions. However, some believe negative WOM are more influential because negative information is rarer than positive information and therefore more diagnostic, which is normally referred as “negativity effect” (Fiske, 1980; Chevalier and Mayzlin, 2006).

Table 4: Estimates of positive and negative WOM's impact on posting behaviour

Variables	Estimate	S.E.
$PosCP_{ubt}$	0.026	0.078
$NegCR_{ubt}$	0.634***	0.113
CR_{ubt}	0.062	0.158
CVR_{ubt}	-7.623	20.42
$PosFP_{ubt}$	1.548***	0.207
$NegFR_{ubt}$	0.281	0.297
FR_{ubt}	0.155*	0.684
FVR_{ubt}	7.322	21.65
$NORC_{ut}$	4.612***	0.137
NOR_{ut}	0.422*	0.183
NOF_u	-0.748*	0.375
T_{ut}	-0.308**	0.093
Variation of baseline tendency		
$\sigma_{\delta_0}^2$	0.208	0.025
Log-Likelihood		-7803
Wald chi2		1402
Prob > chi2		0

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The results in Table 4 shows that only the volume of negative crowd reviews and the positive friend reviews are playing significant roles, while that of the positive crowd reviews and negative friends reviews have no influence. The volume of negative crowd reviews $NegC_{Pubt}$ shows positive significance, which verifies the “negativity effect” (Chevalier and Mayzlin, 2006). Friend review regarding the impact of WOM type shows opposite result. The influential type of friend reviews on the possibility of consumer posting behaviour is positive WOM and the impact is stronger, shown by the coefficient of $PosFP_{ubt}$ (1.548). Such results imply that consumers prefer to engage to evaluate businesses, to which his/her friends have more positive altitude. Therefore, friend recommendations are more influential for consumer purchase intension (Brown and Reingen, 1987) and further engagement on the communications of WOM.

Such results show for the first time the interesting interplay between *PosCP*, *NegCP*, *PosFP*, *NegFP* with the posting possibility. Though it has been widely suggested that both positive and negative WOM have significant impact, such impact largely relies on its source. In particular, the results well explain the finding of the negative influence of the valance of crowd reviews, but positive for friend reviews (Table 3). The volume of negative crowd reviews is shown by Table 4 to be positively correlated to the possibility of posting, while more negative crowd reviews would lead to lower valance. The same logic applies to the friend reviews that large volume of positive reviews leads to high valance.

6. Conclusions and Discussions

6.1. Summary of this work

Consumers frequently look at others to make their own decisions and the eWOM has thus attracted exponential attentions shedding lights for the online marketing and understanding of consumer posting behaviours. While the existing reviews are widely found to be influential, this paper aims to study how friend review and crowd review differently influence subsequent consumer posting behaviour. Assuming the possibility of a consumer posting a review for a particular business is influenced jointly by the consumer characteristics, the volume, valance and variance of friends' and crowds' reviews, we carry out analysis based on multilevel mixed effect probit models on the Yelp data. The major findings are summarised in Table 5. The volume of friend reviews and crowd reviews have both positive impact on the possibility of consumer posting behaviour. The impact of friends' volume is stronger. The valance and variance between friend review and crowd review show opposite effect. The valance and

variance of the crowd reviews have no significant influence when ignoring the friend reviews, but negative influence when considering it. Friend review always has positive impact, but the impact of crowd reviews related to valance and variance is stronger than friends. We also study the impact of sentimental types of WOM on consumer posting behaviour. The positive and negative review volume are separately analysed in the model. We found that the volume of negative crowd review is positively significant for the possibility of consumer posting behaviour, which verifies the “negativity effect”. But the influential type of friend review is positive WOM and the impact is bigger.

Table 5: Summary of findings for consumer engagement in posting behaviour

Hypothesis	Description	Findings	Results
H1a	Volume of crowd review	Positive	Supported
H1b	Volume of friend review	Positive	Supported
H1c	Comparison between the two	friends' review volume is more determinative	Supported
H2a	Valance of crowd review	Negative	Not Supported
H2b	Valance of friend review	Positive	Supported
H2c	Comparison between the two	crowds' review valance is more determinative	Not supported
H3a	Variance of crowd review	Negative	Supported
H3b	Variance of friend review	Positive	Not supported
H3c	Comparison between the two	crowds' review variance is more determinative	Not supported

6.2. Contributions

The findings contribute to the literature in several ways. Firstly, while the consumers' historical behaviours are normally regarded as one of the most influential factor driving them further engage in the posting behaviour, we found that actually their recent behaviour, rather than the history as a whole, strongly influence the posting possibility. Consumer behaviour such as posting and rating always exhibit a strong memory effect (Pan et al., 2014; Hou et al., 2014) that they tend to behave in a certain pattern in a short period. As a consequence, the

number of reviews posted during the past week is found to be the most influential one ($\delta_2 = 4.609$) among all the considered factors. In comparison, the influence of total number of reviews is much weaker with an estimated coefficient $\delta_1 = 0.391$. Secondly, while most studies considered the eWOM in a global way (Flanagin and Metzger, 2013; Chintagunta et al., 2010), we differentiate the eWOM in terms of its sources, i.e. friends or the crowds. The common perception is that the volume, valance and variance of the reviews would largely enhance the possibility of following consumers engaging in the eWOM (Dellarocas et al., 2006). However, such influence shows different effects when considering friends and the crowds separately as different sources of reviews. The influence of the review volume mostly comes from the friends, rather than the crowds. Thirdly, the crowds' reviews highly appreciating the item (high valance) or being more disagreeable (high variance), though are commonly believed to be able to increase the chance of the following posting (Godes and Mayzlin, 2004; Chintagunta et al., 2010), are actually decreasing the posting possibility ($\omega_2, \omega_3 < 0$). Accordingly, we believe that the influence of the past reviews on following posting behaviour comes majorly from the friends. Furthermore, our results provide an explanation of divisive opinions on the impact of WOM types. Some think positive WOM can promote consumer decisions of posting (East et al., 2008; Goldenberg et al., 2007), while others think negative WOM are more influential because negative information are rarer therefore more diagnostic (Fiske, 1980; Chevalier and Mayzlin, 2006). Our findings suggest that both negative and positive WOM are significant, but they come from different sources. For example, the influential negative WOM comes from crowd volume, while positive WOM comes from friend

volume. Overall, these findings may enrich the literature of WOM communities and our comprehensive understanding of consumer posting behaviour.

Managerially, the present paper offers several implications for online marketing and the design of the online user-generated content systems. Firstly, the prior reviews indeed have significant impact on the subsequent consumer decision of whether to post reviews after consumption. A large number of reviews normally associates with flourishing subsequent posting behaviour. On one hand, the system should make the reviews easy accessible for consumers to help them make decisions of consuming and posting. On the other hand, to have thriving reviews should be the one of the priorities for the online marketing, since the popularity of a product is normally self-reinforcing. Secondly, the analysis in this paper highlights the importance of the social networking. Friends' opinions are shown to be more determinative for the possibility of consumer posting behaviour. The posted information is regarded as "sale assistant" (Chen and Xie, 2008) that can largely promote the business sales and consumer engagement on participate in WOM. Accordingly, social network service should be introduced to those online user-generated content systems to facilitate the eWOM. In addition, such finding suggests that it is possibly more efficient to seek for marketing in well established social networks such as Facebook or Twitter (Huberman et al., 2008). Thirdly, while the recommender systems (Hou et al., 2017; Park et al., 2012) are widely developed in online systems, this study suggests that the recommendations from friends should be paid more attentions considering the frequent interactions among them.

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