To follow others or be yourself? Social influence in online restaurant reviews

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Abstract

Purpose – Online reviews are often likely to be socially influenced by prior reviews. This study aims to examine key review and reviewer characteristics which may influence the social influence process.

Design/methodology/approach – Restaurant review data from Yelp.com are analyzed using an ordered logit model and text mining approach.

Findings – This study reveals that prior average review rating exerts a positive influence on subsequent review ratings for the same restaurant, but the effect is attenuated by the variance in existing review ratings. Moreover, social influence is stronger for consumers who had a moderate dining experience or invested less cognitive effort in writing online reviews. Compared to reviewers classified by Yelp as "elite," non-elite reviewers appear more susceptible to the social influence of prior average review rating.

Practical implications – This study provides guidelines for mitigating the social influence of prior reviews and improving the accuracy of online product/service ratings, which will eventually enhance business and the reputation of online review platforms.

Originality/value – The findings from this study contribute to the electronic word-of-mouth (eWOM) literature and social influence literature in terms of the bidirectional nature of social influence on eWOM.

Keywords Social influence, Dining experience, Cognitive effort, Online status, Review variance, Restaurant online review

Paper type Research paper

1. Introduction

Online reviews become increasingly popular as an important source of word of mouth (WOM) (Zhang *et al.*, 2019). Much extant literature assumes that online reviews provide an unbiased perspective on consumers' product experiences (Hu *et al.*, 2011). However, Moe and Schweidel (2012) and Schlosser (2005) argued that, when making one's own rating decision,

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an individual tends to take into consideration opinions expressed by past consumers on review pages and then adjust their own evaluations accordingly, which implies that consumers' online review ratings are possibly socially influenced. According to the anchoring effects in judgment, self-presentation and social conformity theories, online reviewers prefer to consider other consumers' extant opinions when providing their own ratings (Adomavicius *et al.*, 2013). Yet, previous literature offers limited understanding regarding the social influence process of consumers' online review behavior, especially the factors that may influence (i.e. strengthen or weaken) this process. The literature on experience-oriented hospitality products is especially scarce.

Based on the following comprehensive literature review, several research gaps are identified. First, consumers' product/service experiences can be heterogeneous, ranging from extremely positive or negative to moderately positive or negative. The social categorization literature suggests that compared to moderate-strength cues, extreme cues are considered more diagnostic and less ambiguous (Reeder and Brewer, 1979; Skowronski and Carlston, 1989). Therefore, the degree to which heterogeneous product/service experiences are socially influenced by prior review ratings may differ. Second, according to the social influence theory and the elaboration likelihood model (ELM), a consumer's online status matters and may affect other consumers' decision-making process when rating a product/service. Researchers (Ma *et al.*, 2013; Moe and Schweidel, 2012) empirically tested the moderating effect of a user's review experience (measured by the number of reviews written by the reviewer) and found that consumers who wrote fewer reviews previously are more likely to be socially influenced by prior review ratings. Nonetheless, the role of a reviewer's online status, which reflects the reviewer's expertise based on prior review quantity and quality (i.e. being labeled an expert – or not – on an online review website), has not been examined in extant literature. Third, according to ELM, consumers who invest more cognitive effort into writing reviews are more likely to take a central thinking route. Ma *et al.* (2013) used review length to measure the cognitive effort invested in review writing and discovered that longer reviews can reduce the extent of social influence from prior reviews. However, review length is limited in representing cognitive efforts; further content and linguistic analyses of review text are needed to better examine a reviewer's cognitive effort.

On this basis, understanding the factors that shape consumers' online review-rating behavior is essential. The purpose of an online review reputation system is to provide trustworthy and high-quality evaluations of products/services (Ma *et al.*, 2013). Therefore, highlighting socially influenced online reviews or filtering out biases is critical for reputation systems and for consumers seeking to make well-informed purchase decisions. Given the importance of online review accuracy to consumers and companies, this study examines several measurable conditions under which subsequent review ratings are more likely to be socially influenced. By using online restaurant review data from Yelp, this study investigates whether and how prior review ratings from other consumers affect a focal consumer's online review rating regarding experience-oriented products such as restaurant dining. In addition, this study examines the extent to which a consumer's dining experience, cognitive effort in writing a review, online status and the variance of prior review ratings influence his/her subsequent online restaurant review-rating behavior.

2. Literature review

Recent literature suggests that a consumer's subsequent review can be influenced by prior reviews he/she reads (Lee *et al.*, 2015; Schlosser, 2005; Wang *et al.*, 2018), which may bias online product review ratings. Moe and Trusov (2011) noted that an online product rating is composed of the customer's actual consumption experience and social influence from prior reviews. Some literature suggests that subsequent review ratings tend to imitate prior ratings, similar to a herding effect (Adomavicius, *et al.*, 2013; Ma *et al.*, 2013). Other scholars reported that subsequent reviews tend to be differentiated from prior review ratings, demonstrating a differentiation effect (Hu and Li, 2011; Moe and Trusov, 2011). To address this contradiction, researchers have recently begun to examine the diverse impacts of prior review ratings given that reviewers and reviews are heterogeneous. Relevant literature is summarized in Table I, organized and classified by factors affecting the social influence process of online reviews (e.g. reviewer characteristics and review characteristics).

3. Research hypotheses

3.1 Impact of prior reviews on subsequent review ratings

Consumers usually check product reviews online before making purchases, which inform their pre-purchase expectations (Ho *et al.*, 2017). Moreover, when customers visit a webpage or social media to post an online review after making a purchase, they are also exposed to prior reviews and ratings from past customers (Schlosser, 2005). Moe and Trusov (2011) and Lee *et al.* (2015) stated that an online product rating reflects a customer's real consumption experience and the degree of social influence on the consumer.

Social influence theory contends that people tend to experience conformity pressure from other group members (Cialdini and Goldstein, 2004). According to anchoring effects in judgment (Chapman and Johnson, 2002), people may apply an anchoring-and-adjustment heuristic when making a decision. The decision-maker may begin with an initial value and make adjustments to reach a final choice. Specifically, other consumers' average rating constitutes an anchor or initial value, and then the focal consumer makes corresponding modifications according to the perceived disconfirmation based on his/her consumption experience. This leads the decision-maker's final judgment to be skewed toward the anchor, as the anchoring effect tends to bias the retrieval of previous experiences consistent with the initial anchor; anchoring effects in judgment are even more prominent when the experience/preference is recalled (Adomavicius *et al.*, 2013). Adomavicius *et al.* (2013) also found that a recommendation system rating tends to elicit anchoring bias and can significantly influence subsequent consumers' ratings of a product/service. Therefore, a consumer's online review rating is likely to be influenced by prior review ratings posted by other consumers. On this basis, the following hypothesis is proposed:

H1. The prior average review rating has a positive influence on the subsequent ratings of the same restaurant.

3.2 Role of consumer's product experience

A consumer's product experience can be heterogeneous, ranging from extreme to moderate. Most judgments, such as likes or dislikes, imply an array of ratings with the level of judgment ambiguity determining the width of this range (Birnbaum, 1972). When an individual has a moderate product experience with simultaneous positive and negative attributes, he/she is more likely to encounter uncertainty when quantifying the item's quality; that is, the consumer may struggle to measure and rate the product quality on a scale of 1-5 (or 1-10). Consequently, the consumer may search starting from the anchor to the plausible value in a distribution of uncertain values, leading to a final value that skews toward the anchor (Jacowitz and Kahneman, 1995). Adomavicius *et al.* (2013) argued that online review rating systems are susceptible to anchoring bias, which can influence subsequent consumers' product evaluations. The correspondence judgment literature states

Authors	Research context	Method	Findings
Reviewer characteristics			
Wang *et al.* (2018)	Reviews of books, movies and music	Quasi-experiment (difference-in-difference)	Friend relationships can significantly improve online users' rating similarity. Social influence is stronger for consumers with smaller online networks and for older books. More recent and extremely negative reviews have stronger impact than other reviews
Zhang *et al.* (2016)	Hotel reviews collected from Qunar.com	Econometric model: ordered logit model and Bayesian ordered logit model	The number of online user-generated "expert reviews" has a positive influence on subsequent reviewers' ratings, whereas the marginal effect decreases. Reviewing expertise can strengthen this positive effect
Lee *et al.* (2015)	Movie reviews on several public websites	Two-stage econometric models: selection model and rating model (following Moe and Schweidel, 2012)	Friends' ratings can induce a herding effect (i.e. an individual reviewer tends to imitate his/her friends' ratings), and a larger number of friends has a positive effect on review ratings. However, herding and differentiation effects influence crowd ratings (i.e. an individual reviewer tends to either imitate or differentiate him/herself from other strangers' ratings), depending on film popularity
Ma *et al.* (2013)	A panel data set of 61,029 reviews by 744 reviewers on Yelp	Econometric model: ordered probit model and Markov chain Monte Carlo simulation method	Male reviewers lacking review experience, social connection or geographic mobility are more likely to be socially influenced by previous review ratings
Moe and Schweidel (2012)	Reviews of bath, fragrance and home products from an online retailer	Two-stage econometric model: selection model and rating model	Less frequent reviewers tend to imitate prior review ratings, and frequent reviewers tend to differentiate themselves by posting relatively negative ratings
Review attributes			
Li *et al.* (2019)	Online restaurant reviews	Econometric model: ordered logit model	Consumers' review rating is influenced by prior average review rating and number of prior reviews, while review temporal distance can strengthen the influence of prior reviews
Ma *et al.* (2013)	A panel data set of 61,029 reviews by 744 reviewers on Yelp	Econometric model: ordered probit model and Markov chain Monte Carlo simulation method	More frequent and longer reviews tend to reduce the social influence of prior reviews
Moe and Schweidel (2012)	Reviews of bath, fragrance and home products from an online retailer	Two-stage econometric model: selection model and rating model	Positive ratings environments increase an individual's review-posting probability whereas negative ratings environments decrease it
Hu and Li (2011)	Book reviews on Amazon.com	Econometric model, specifically the ordered logistic model	When product quality is controlled, subsequent review ratings tend to be differentiated from prior review ratings; this relationship is moderated by book

(*continued*)

Table I.
Summary of previous literature

Authors	Research context	Method	Findings
			popularity, variance of prior review ratings and whether subsequent reviews mention previous reviews
Moe and Trusov (2011)	Reviews of bath, fragrance and beauty products of an online retailer	Econometric model	Subsequent review ratings tend to be differentiated from prior review ratings. Discrepancies among prior raters discourage subsequent raters to post extreme opinions
Schlosser (2005)	Movie reviews	Laboratory experimental design	Reviewers who are expected to post their product experiences on the internet lower their online product ratings after reading others' negative reviews with the motivation of being perceived as discriminating or an expert, while no influence appears after reading positive reviews. Reviewers are more likely to present more than one side opinions than lurkers when they observe heterogeneous prior reviews
Others			
Adomavicius *et al.* (2013)	Television shows or jokes	Laboratory experimental design	The rating displayed by a recommendation system can be an anchor, which influences viewers' preference ratings. This influence is also affected by perceived reliability of a recommendation system
Muchnik *et al.* (2013)	Social news aggregation website	A large-scale randomized experiment	Prior ratings exert social influence on subsequent individuals' rating behavior. For negative social influence, reviewers tend to correct biased ratings; positive social influence improves the positive ratings' probability and subsequent review ratings increased by averagely 25%. However, social influence is topic-dependent and influenced by whether opinions of friends or enemies are observed
Sridhar and Srinivasan (2012)	Hotel reviews (7,499 reviews among 114 hotels)	Econometric model, specifically the nested ordered logistic model	Other consumers' review ratings moderate the effect of the focal consumer's product experience on his/her review rating for this product. The average review ratings of other consumers can weaken the relationship between "positive and negative attributes of product experience" and the consumer's review rating, while could strengthen or attenuate the negative impact of product failure on his/her rating, depending on the success of product recovery

Table I.

that people are more confident in using highly salient information, e.g. extreme opinions, which are often integrated into more formal judgments (Kruglanski, 1989). Previous research also shows that the uncertainty of an individual's judgment corresponds to a strong social influence, whereas certainty decreases social influence substantially

(Cialdini, 2009; Cialdini and Goldstein, 2004). For instance, Hoch and Ha (1986) found that when consumers encounter ambiguous evidence, their product quality judgment is dependent upon objective physical evidence as well as the dramatic influence imposed by advertising.

In contrast, according to the goal-based emotion literature, affective reactions of high intensity (e.g. extreme opinions) are only generated around important individual goals (Lazarus and Folkman, 1984). Extreme judgments tend to be perceived as less ambiguous compared to moderate judgments, as extreme values are located at the scale's end-point and thus only have a constricted range (Gershoff *et al.*, 2003). When consumers have an extreme product experience, whether highly positive or highly negative, they are more likely to be certain in quantifying the quality on a scale of 1-5 (or 1-10). As such, regardless of other consumers' ratings, the focal consumer tends to quantify his/her experience with certainty (i.e. assigning a rating of "1" for an extremely negative experience or "5" for an extremely positive experience). In these cases, people may overlook conformity pressure and behave altruistically for the benefit of the group (Hornsey, 2006).

The social categorization literature indicates that compared to cues of extreme strength, moderate cues are perceived as more ambiguous and less reliable (Reeder and Brewer, 1979; Reeder *et al.*, 1982). When consumers have an extremely positive or extremely negative experience that disconfirms existing reviews and ratings, they are more likely to experience normative conflict and neglect conformity pressure if they believe doing so is better for the group (Ashforth *et al.*, 2000; Li *et al.*, 2019). In this scenario, people are less likely to be socially influenced and will be motivated by either concern for other consumers or an interest in helping the company by expressing a true product experience (Hennig-Thurau *et al.*, 2004). Therefore, the following hypothesis is proposed:

H2. The influence of prior average review rating on subsequent ratings of the same restaurant is moderated by a consumer's dining experience; the influence is stronger when the consumer has a moderate dining experience and weaker when the consumer has an extreme dining experience, either highly positive or highly negative.

3.3 Role of consumer's cognitive effort

Cognition refers to "the mental action or process of acquiring knowledge and understanding through thought, experience, and the senses" (Oxford Dictionary, 2018). An individual's attempt to understand consumption experiences involves multiple cognitive processes, such as analytical writing (Lyubomirsky *et al.*, 2006) and explanation (Moore, 2012). The cognitive processes can help people understand the causes and outcomes of their product/service experiences (Moore, 2012; Wilson and Gilbert, 2008). Joksimovic *et al.* (2014) found that participants exhibit better understanding if they are engaged in higher cognition and emotions while journaling about an experience. According to the social conformity theory (Cialdini and Goldstein, 2004), if individuals expend little cognitive effort when processing a message, they are highly likely to use an accuracy heuristic favoring the group majority. Conformity, thus, could be the outcome of less-mindful activation of two conformity motivations, accuracy and affiliation, at little cost to cognitive resources (Cialdini and Goldstein, 2004). According to ELM, consumers who invest extensive cognitive efforts when writing a product review intend to take a central route of thinking and thus rely less on other consumers' reviews and ratings when providing their own (Ma *et al.*, 2013).

The psychology literature has considered language and words to be reflective of cognitive effort and process (Joksimovic *et al.*, 2014). When individuals use cognitive mental processes in drafting online reviews, their comments exhibit a significant increase in words related to logical and analytical thoughts, such as *because*, *therefore* and *think* (Ma *et al.*, 2013). The presence of cognitive words in online reviews reflects the reviewer's analytical thought process and his/her active attempt to understand the experience, constituting a valid representation of the reviewer's underlying cognitive process (Boals and Klein, 2005). The following hypothesis is thus proposed:

H3. The influence of prior average review rating on subsequent ratings of the same restaurant is moderated by the consumer's cognitive effort in writing the online review; the influence is stronger for the consumer who invests less cognitive effort in writing the review, and weaker for the consumer investing more cognitive effort.

3.4 Role of consumer's online status

Given that consumers are heterogeneous in their online review experience, research has begun to examine the different impacts of prior review ratings on consumers' online evaluations among different reviewers. According to ELM (Petty *et al.*, 1983), individuals possess two routes for information processing: the peripheral route and the central route. ELM suggests that people who are more experienced tend to use the central route to process information and are less likely to be influenced by others. Those who are inexperienced are more likely to rely on others' opinions for reference when making a final decision (i.e. the peripheral route). Studies report that consumers with less review experience (measured by their number of reviews written previously) tend to mimic prior review ratings; whereas consumers with more review experience are more likely to post relative negative review ratings to differentiate themselves from others (Ma *et al.*, 2013; Moe and Schweidel, 2012).

Most online review websites and social media platforms have developed a reviewers' credential profile. Yelp has maintained such a profile that can denote reviewers as "Elite" if they have contributed substantially to the platform. The "Elite" label is not based solely on the number of reviews an individual writes but also on well-written reviews, high-quality photos and tips, active voting behavior and a history of being cordial to other users (Yelp, 2017). Connors *et al.* (2011) found that reviews written by elite reviewers provide deeper insight into a product/service and are deemed more helpful. Hochmeister *et al.* (2013) contended that most destination experts in online travel communities write reviews about more than one destination. They are also likely to be more experienced and have belonged to the community for longer than general reviewers. Compared to non-expert reviewers, experts often know more about a given product/service's intricacies and are better prepared to evaluate and recall their detailed experiences (Ma *et al.*, 2013). A recent study by Zhou and Guo (2017) found that higher-order reviews tend to be more susceptible to social influence than lower-order reviews from prior reviewers; thus, the order of a review appears negatively associated with review helpfulness. However, this negative effect is weakened when the reviewer has a higher degree of expertise or is more socially connected. Therefore, we propose that in addition to a reviewer's reviewing experience (as measured by the number of reviews previously written), a consumer's online status reflecting expertise (i.e. whether he/she is an expert) moderates the effect of prior reviews on subsequent review ratings:

H4. The influence of prior average review rating on subsequent ratings of the same restaurant is moderated by consumers' online status; the influence is stronger when the consumer is not labeled an expert by the online review platform and weaker when the consumer is labeled an expert by the online review platform.

3.5 Role of variance in prior review ratings

Major e-commerce and online review websites, such as Amazon and Yelp, display the average rating of all consumers' reviews along with rating distributions, depicted by a bar chart indicating the number/proportion of each rating level (Sun, 2012). The bar chart often appears in a prominent location on the product introduction page and is likely to be seen by a customer/reviewer who may then be influenced by the distribution or variance of prior review ratings. According to the extant literature, variance in online reviews (Sun, 2012; Zhu and Zhang, 2010) can affect consumers' purchase intentions, online product sales and firms' financial performance.

The dispersion of online review ratings reflects reviewers' degree of consensus and provides information on the accuracy of the average rating (Yin *et al.*, 2016). Based on Bayesian information updating theory (Gelman *et al.*, 2013), Hu and Li (2011) argued that among various information sources, those with lower variance exert greater impacts on consumers. In other words, highly dispersed review ratings reduce consumers' confidence in the certainty of the average rating (Petrocelli *et al.*, 2007). According to the social conformity theory, consumers are more likely to be influenced by their peers who share an opinion (Feldman, 2003). For example, consumers form an initial expectation about a hotel upon reading the average review rating, but this initial expectation could be attenuated when consumers are less certain about their initial beliefs (e.g. in the case of low review volume or high review dispersion). However, little is known about how online review rating distributions influence the impact of prior reviews on subsequent ratings, especially for restaurant online reviews. As such, the following hypothesis is proposed:

H5. The influence of prior average review rating on subsequent ratings of the same restaurant is moderated by the variance in existing ratings; the influence is stronger when the variance is low and weaker when the variance is high.

The research framework is summarized in Figure 1.

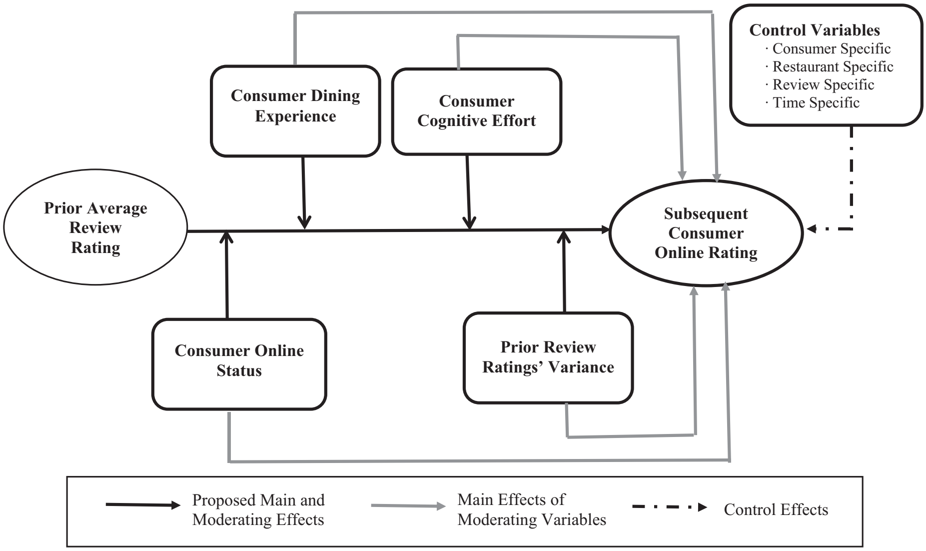

Figure 1.
Conceptual framework

4. Research method

4.1 Data

This study examines the restaurant setting, rather than manufactured goods, given that restaurant products are more experience-oriented with characteristics of intangibility, variability, perishability and inseparability. Restaurant review data were collected from Yelp.com, one of the largest online review communities in the USA focusing on local businesses, especially restaurants. On Yelp, consumers post online reviews onto a restaurant's information page, where they are exposed to prominent review characteristics such as the restaurant's overall rating, number of reviews and review rating distribution. Las Vegas was selected as the target setting given that the city is one of the top tourism destinations in the world, and most reviewers are visitors who are more likely to check reviews posted by other reviewers.

A crawler was developed to download restaurant Web pages automatically, and a parser was created to parse the HTML/XML Web pages into the database. The authors chose the most-popular 300 restaurants (measured by the number of online reviews) in Las Vegas to ensure a sufficient number of reviews per restaurant and to include various types of ethnic cuisines (Li *et al.*, 2017). All reviews posted on and before January 8, 2015 for these 300 restaurants comprised the data set, resulting in 186,714 reviews. The sample also included all price ranges in restaurants: inexpensive (n = 42, 13.96 per cent), moderate (n = 184, 61.39 per cent), pricey (n = 52, 17.26 per cent) and ultra-high-end (n = 22, 7.39 per cent). The data set included three levels of data (i.e. review-level, reviewer-level and restaurant-level data), which were all merged into the final data set.

4.2 Variable operationalization

To assess the effects of prior average review rating on subsequent ratings of the same restaurant, a series of variables were incorporated and measured in the model. The dependent variable was the reviewer's online rating of the restaurant (y_{ijt}). Other variables are as follows:

Prior average review rating: The average of prior restaurant review ratings before the current review (the nth review) was used to measure social influence (Sridhar and Srinivasan, 2012), taken as the average rating of the first, second, [. . .], and ($n-1$)th review ratings for restaurant j ($AveOthers_{jt}$). Rather than the exact restaurant rating, the rounded average review rating to the nearest half-star was used (Ma *et al.*, 2013). The rounded average rating is consistent with that displayed on Yelp and allows the authors to accurately test the social influence of prior review ratings.

Consumer's dining experience: Consistent with Sridhar and Srinivasan (2012) and Ma *et al.* (2013), words/emotions in online review text reflect consumers' real product experiences. Previous literature reveals that online review ratings may not fully represent consumers' experiences and satisfaction. Indeed, review ratings are likely to be influenced by several factors beyond the actual experience (De Langhe *et al.*, 2015; Jiang *et al.*, 2010). Therefore, in this study, consumer experience ($ConsExp_{ijt}$) was measured by the sentiment index of a textual review. Specifically, we calculated review sentiment using a naïve Bayesian algorithm, one of the most common categorization methods. The values of review sentiment ranged from 0 to 1; the higher the sentiment value, the more positive the experience. Consumer experience in this study was coded as 1 if the value was smaller than 0.05, denoting an extremely negative experience; it was coded as 2 if the value was larger than 0.95, denoting an extremely positive experience; otherwise, it was coded as 0. Details about our calculation process for review sentiment, with accompanying examples with different sentiment values, can be found in Appendices 1 and 2.

Cognitive effort: The latest version of the Linguistic Inquiry and Word Count (LIWC) program, a text mining tool, was used to analyze the percentage of cognitive process words (e.g. *because*, *cause*, *know* and *ought*) in the body of each review (Pennebaker *et al.*, 2007), especially causal (e.g. *because* and *hence*) and insight-related words (e.g. *consider*, *think* and *know*). The LIWC program calculates the percentage of words matched to pre-defined dictionaries in a text (Pennebaker *et al.*, 2007). More cognitive-related words in review text suggest that more cognitive efforts were devoted to review writing.

Consumer online status: Consumer online status was coded as 1 if the consumer was an elite reviewer in the year the review was written; otherwise, it was coded as 0.

Variance of prior review ratings: The variance of prior review ratings ($ReviVar_{jt}$) was measured by the variance of the first, second, [...], and ($n - 1$)th review ratings for restaurant j (before current review n).

Control variables: To ensure an unbiased estimation, the authors needed to control for all other alternative explanations, including review-, reviewer-, restaurant- and time-level variables. The details for each variable are listed in Table II. The distribution of customer review ratings (dependent variable) is shown in Figure 2.

Variable	Description
Dependent variable	
y_{ijt}	Review rating provided in review i for restaurant j at time t
Independent variable	
$AveOthers_{jt}$	The prior average review rating for restaurant j at time t (before the current review)
Control variables (The direct effects of all moderating variables are also controlled)	
(1) Review-level	
$Length_{ijt}$	Total number of words in review i for restaurant j at time t
(2) Reviewer-level	
$Tenure_{it}$	Number of months since the consumer registered on Yelp when review i was written at time t
(3) Restaurant-level	
$Popularity_{jt}$	Number of reviews for restaurant j at time t (before the current review)
$Price_j$	A categorical variable classifying restaurants into different price ranges (1 = inexpensive; 2 = moderate; 3 = pricey; and 4 = ultra-high-end)
$Category_j$	A categorical variable classifying restaurants into different categories, such as American, Mexican or Chinese (n = 178)
(4) Time-level	
$Year_{ijt}$	Year in which review was written (reference year = 2005)
$Month_{ijt}$	Month in which review was written (reference year = January)
Moderating variables	
$ConsExp_{ijt}$	Consumer i's experience extremity for restaurant j at time t (1 = sentiment value smaller than 0.05; 2 = sentiment value larger than 0.95; otherwise, equals 0)
$Congitive_{ijt}$	Consumer i's cognitive effort, measured by the proportion of cognitive process words (e.g. *because*, *cause*, *know* and *ought*) in each review text by consumer i for restaurant j at time t
$Status_{it}$	Consumer i's online status, measured by whether consumer i was labeled "Elite" in year t when writing a review (yes = 1; and no = 0)
$Variance_{jt}$	Variance of review ratings for restaurant j at time t (before the current review)

Table II.
Variable operations

4.3 Econometric model

To evaluate the overall restaurant quality, the Yelp community uses a product rating system with an integer value ranging from 1 to 5. Because the dependent variable was ordinal and consisted of censored data, an ordered logit model was used in this study (Cameron and Trivedi, 2005). The basic analytic unit was the review. Consider a review rating y_{ijt} = {1,2,3,4,5}, which is the rating score written by consumer i (i = 1, . . ., I) for restaurant j (j = 1, . . ., J) at time t. Let y_{ijt}^* be the latent variable that represents the consumer's restaurant evaluation. y_{ijt}^* is specified as a function of different factors that can affect the customer's evaluation as follows:

$$\begin{aligned} y_{ijt}^* = {} & \alpha_0 \mathrm{AveOthers}_{jt} \\ & + \beta_1 \mathrm{ConsExp}_{ijt} + \beta_2 \mathrm{Cognitive}_{ijt} + \beta_3 \mathrm{Status}_{it} + \beta_4 \mathrm{Variance}_{jt} \\ & + \gamma_1 \mathrm{AveOthers}_{jt} \times \mathrm{ConsExp}_{ijt} + \gamma_2 \mathrm{AveOthers}_{jt} \times \mathrm{Cognitive}_{ijt} \\ & + \gamma_3 \mathrm{AveOthers}_{jt} \times \mathrm{Status}_{it} + \gamma_4 \mathrm{AveOthers}_{jt} \times \mathrm{Variance}_{jt} \\ & + \theta' Z_{ijt} + \varepsilon_{ijt} \end{aligned} \tag{1}$$

where Z_{ijt} represents the other control variables described above, and ε_{ijt} is an error term with a logistic distribution of $F(z) = e^z/(1+e^z)$.y_{ijt}* crosses a series of increasing unknown thresholds, so the ordering of alternatives moves up accordingly. The ordered model in this study is defined as follows (Cameron and Trivedi, 2005):

$$\begin{aligned} \Pr[\mathrm{Rating}_{ijt} = j] &= \Pr\left[\alpha_{m-1} < y_{ijt}^* < \alpha_m\right] \\ &= \Pr\left[\alpha_{m-1} < x_{ijt}'\beta + u_{ijt} < \alpha_m\right] \\ &= \Pr\left[\alpha_{m-1} - x_{ijt}'\beta < u_{ijt} < \alpha_m - x_{ijt}'\beta\right] \\ &= F\left(\alpha_m - x_{ijt}'\beta\right) - F\left(\alpha_{m-1} - x_{ijt}'\beta\right) \end{aligned} \tag{2}$$

where F is the *cdf* of u_{ijt}, and α_m (threshold values) and β (regression parameters) will be obtained by applying the maximum log-likelihood estimation method.

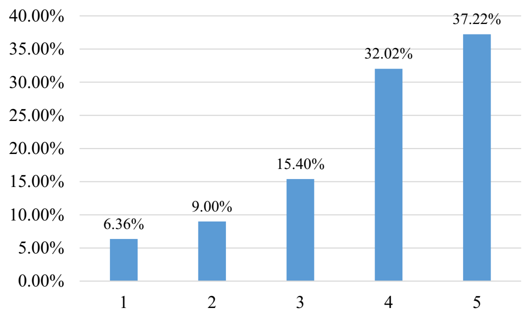

Figure 2. Distribution of customer review ratings (1-5 star)

5. Empirical results

5.1 Main results

The estimation results of the ordered logit model are shown in Table III. Model 1.1 included a series of control variables as the independent variables. Model 1.2 tested the effect of the prior average review rating on the subsequent review rating while controlling all control variables included in Model 1.1. Model 1.3 was the full model incorporating Model 1.2 and further tested the moderating effects of the consumer's experience, cognitive effort, online status and variance of prior review ratings. The estimation results among the three models were consistent. Model 1.3 had the highest pseudo R^2 value (0.1601) and was thus used in the following sections to explain the final estimation results.

According to Model 1.3 (Table III), the effect of prior average review rating exerted a significant and positive influence on the subsequent restaurant rating (coefficient = 1.451363); hence, *H1* was supported. The influence of the prior average review rating on the subsequent rating was negatively moderated by the consumer's experience (extreme negative experience: coefficient = −0.5802659, $p < 0.000$; extreme positive experience: coefficient = −0.1900039, $p < 0.000$). In other words, the social influence of prior average

	Model 1.1	Model 1.2	Model 1.3
AveOthers		1.128559*** (0.0150197)	1.451363*** (0.0479882)
ConsExp			
Low (= 1)			−0.0511321 (0.1171615)
High (= 2)			2.017633*** (0.0834556)
ConsExp × *AveOthers*			
Low (= 1) × AveOthers			−0.5802659*** (0.0312033)
High (= 2) × AveOthers			−0.1900039*** (0.0215297)
Cognitive			−0.0123731 (0.0082127)
Cognitive × AveOthers			−0.0115263*** (0.0021199)
Status			0.5139996*** (0.0831501)
Status × AveOthers			−0.1607279*** (0.0215101)
Variance			0.4374829*** (0.1142373)
Variance × AveOthers			−0.1492984*** (0.0295331)
Length	−0.0016519*** (0.0000367)	−0.0017552*** (0.0000369)	−0.0012144*** (0.0000401)
Tenure	−0.0031177*** (0.0002348)	−0.0032814*** (0.0002356)	−0.0031168*** (0.0002502)
Popularity	−0.00005*** (0.000012)	−0.0001243*** (0.0000121)	−0.0001024*** (0.0000125)
Price			
Price = 2	−0.5382833*** (0.033001)	−0.1339934*** (0.0336871)	−0.2063145*** (0.035647)
Price = 3	−0.0715256* (0.0386503)	0.0874415** (0.0388968)	−0.0911626** (0.0412116)
Price = 4	−0.0508706 (0.0465049)	0.0660336 (0.046919)	−0.092124* (0.0490198)
Restaurant category	Yes	Yes	Yes
Review year FE	Yes	Yes	Yes
Review month FE	Yes	Yes	Yes
/cut-1	−2.756608* (1.514044)	1.788264*** (0.3372759)	2.093023*** (0.5202077)
/cut-2	−1.725567 (1.514026)	2.834868*** (0.337251)	3.470285*** (0.5201699)
/cut-3	−0.7566665 (1.514017)	3.825315*** (0.3372979)	4.809533*** (0.5202089)
/cut-4	0.7099148 (1.514018)	5.325628*** (0.3374146)	6.613248*** (0.5203075)
Observations	186,566	186,256	185,969
Pseudo R^2	0.0432	0.0540	0.1601
LR chi-square	22757.49	28443.46	84143.82
Prob > chi-square	0.0000	0.0000	0.0000
LL	−252184.9	−248943.93	−220701.4

Notes: Values in parentheses indicate standard errors. Asterisks indicate the coefficient is significant at: *10; **5 and; ***1% level

Table III.
Estimation results – ordered logit model

review rating was weaker when the consumer had either an extreme negative experience or an extreme positive experience, and social influence was stronger when the consumer's dining experience was moderate; thus, *H2* was supported.

Regarding the role of consumer cognitive effort, the estimation results demonstrate that the moderating effect was significant but negative (coefficient = −0.0115263), indicating that the social influence from the prior average review rating was weaker when a consumer invested substantial effort in writing the review. Social influence was stronger when a consumer devoted less effort. *H3* was therefore supported.

For reviewer online status, the estimation results demonstrate a significantly negative moderation effect (coefficient = −0.1607279, $p < 0.01$), indicating that non-elite reviewers were more likely to be socially influenced by the prior average review rating, whereas elite reviewers were less likely to be socially influenced; therefore, *H4* was supported. The moderating effect of the variance in existing review ratings was found to be significant and negative (coefficient = −0.1492984). The influence was thus stronger when the variance of existing restaurant review ratings was low and weaker when the variance was high, which supported *H5*.

Estimation results regarding the influences of control variables on a consumer's online restaurant review rating were consistent and robust in Models 1.1-1.3. In Model 1.3, review length had a significant and negative influence on a consumer's online review rating (coefficient = −0.0012144), indicating that consumers may write more in online reviews when complaining about an unpleasant dining experience. The effect of consumers' tenure on Yelp also showed a significantly negative influence on the consumer's online review rating (coefficient = −0.0031168); that is, consumers who had been members of Yelp for a longer time were more likely to assign a lower rating to a restaurant. In addition, the number of prior review ratings exerted a significantly negative impact (coefficient = −0.0001024, $p < 0.001$), implying that the restaurant review rating decreased with an increase in the number of online reviews. This result is consistent with the self-selection bias proposed by Li and Hitt (2008), noting that early consumers self-select products they believe they may enjoy, and thus tend to provide higher ratings compared to subsequent consumers and the general population.

5.2 Robustness check

Alternative operations of variable: To examine the model's robustness, the sensitivity of the estimation results to different operations of consumer product experience was checked using two alternative operations. First, consumer experience was coded as 1 if the value was smaller than 0.01, meaning extreme negative experience; it was coded as 2 if the value was larger than 0.99, meaning extreme positive experience; otherwise, it was coded as 0. Second, consumer experience in this study was coded as 1 if the value was smaller than 0.10, meaning extreme negative experience; it was coded as 2 if the value was larger than 0.90, meaning extreme positive experience; otherwise, it was coded as 0. Then, the new models were re-estimated by replacing consumer experience with the above two alternative operations. Results in Table IV were quantitatively similar to those in Table III.

Robustness test using restaurant fixed effects: In addition to the price and restaurant categories, which may affect a consumer's online review rating, other restaurant-level variables (e.g. location, parking and transportation) could also influence a consumer's evaluation. To avoid estimation bias, another robustness check was conducted by replacing restaurant-level variables of price and category with restaurant fixed effects to help control for unobserved time invariant heterogeneity. Estimation results were listed in Table V and were quantitatively similar to the main estimation results.

	Model 2.1 (0.01, 0.99)	Model 2.2 (0.10, 0.90)
AveOthers	1.452006*** (0.0468424)	1.410545*** (0.0488862)
ConsExp		
Low (= 1)	−0.1556163 (0.1283528)	−0.0979475 (0.1165062)
High (= 2)	2.153921***(0.0794366)	1.852866*** (0.0894302)
ConsExp × AveOthers		
Low (= 1) × AveOthers	−0.63068*** (0.0343093)	−0.5130765*** (0.0309526)
High (= 2) × AveOthers	−0.227879*** (0.0204043)	−0.1407263*** (0.0231411)
Cognitive	−0.0101047 (0.0082058)	−0.016944** (0.0082024)
Cognitive × AveOthers	−0.0127141*** (0.0021177)	−0.0099128*** (0.0021177)
Status	0.5316952*** (0.0828544)	0.5038634*** (0.0832294)
Status × AveOthers	−0.1668433*** (0.021439)	−0.1556435*** (0.021529)
Variance	0.4273666*** (0.1139828)	0.4426208*** (0.1141778)
Variance × AveOthers	−0.1486759*** (0.0294648)	−0.1525343*** (0.0295325)
Length	−0.0014508*** (0.0000407)	−0.001119*** (0.0000398)
Tenure	−0.0032291*** (0.0002502)	−0.0030419*** (0.0002501)
Popularity	−0.0000954*** (0.0000125)	−0.0001071*** (0.0000125)
Price		
Price = 2	−0.2058639*** (0.0355588)	−0.2147045*** (0.0356891)
Price = 3	−0.0940282** (0.0411259)	−0.0912189** (0.0412515)
Price = 4	−0.0815797* (0.0489564)	−0.0848535*(0.0490237)
Restaurant category	Yes	Yes
Restaurant FE	No	No
Review year FE	Yes	Yes
Review month FE	Yes	Yes
/cut-1	1.760366*** (0.514159)	2.090215*** (0.5155481)
/cut-2	3.119931*** (0.5141095)	3.461095*** (0.5155182)
/cut-3	4.411374*** (0.5141292)	4.811582*** (0.5155656)
/cut-4	6.18729*** (0.5142289)	6.62361*** (0.5156594)
Observations	185969	185,969
Pseudo R^2	0.1523	0.1614
LR chi-square	80032.72	84834.02
Prob > chi-square	0.0000	0.0000
LL	−222756.95	−220356.3

Table IV. Estimation results – alternative measurement for *ConsExp*

6. Conclusion and discussion

6.1 Conclusions

Using online restaurant review data from Yelp, this study examined whether and how prior review ratings posted by other consumers affect a subsequent consumer’s online review when evaluating an experience-oriented product such as a restaurant. In addition, this study investigated the roles of consumer experience, cognitive effort in writing a review, online status and variance of prior review ratings in consumers’ restaurant online reviews. The authors applied social influence and online WOM literature to formulate hypotheses and tested them using a large online data set and text mining approach.

The empirical results indicate that:

- Prior average review rating exerts a positive influence on subsequent review ratings of the same restaurant.
- The influence of prior average review ratings on subsequent ratings is stronger when the consumer has a moderate dining experience or when he/she invests less cognitive effort in writing the review; whereas the influence is weaker when the

	Model 3.1 (0.95, 0.05)	Model 3.2 (0.99, 0.01)	Model 3.3 (0.90, 0.10)
AveOthers	0.8673359***	0.8587205*** (0.053343)	0.8343061*** (0.0551583)
ConsExp			
Low (= 1)	−0.0572254 (0.1171526)	−0.1614351 (0.1283907)	−0.1045452 (0.1165009)
High (= 2)	2.033943*** (0.0839782)	2.177803*** (0.0800483)	1.865575*** (0.0898701)
ConsExp × *AveOthers*			
Low (= 1) × *AveOthers*	−0.5780882*** (0.031206)	−0.6282594*** (0.0343235)	−0.5106914*** (0.0309558)
High (= 2) × *AveOthers*	−0.1927172*** (0.021666)	−0.2322177*** (0.0205621)	−0.1428145*** (0.0232573)
Cognitive	−0.0144061* (0.0082436)	−0.0120238 (0.0082369)	−0.0187978** (0.008234)
Cognitive × *AveOthers*	−0.0110753*** (0.0021278)	−0.0122827*** (0.0021257)	−0.009515*** (0.0021258)
Status	0.4436789*** (0.0834408)	0.4605722*** (0.0831559)	0.434039*** (0.08352)
Status × *AveOthers*	−0.1391766*** (0.0215901)	−0.1451602*** (0.0215217)	−0.1342107*** (0.0216088)
Variance	0.5520251*** (0.134435)	0.5164394*** (0.1337551)	0.5760351*** (0.134285)
Variance × *AveOthers*	−0.1976034*** (0.0357003)	−0.1905214*** (0.0355254)	−0.2039917*** (0.0356785)
Length	−0.0013245*** (0.0000404)	−0.0015605*** (0.000041)	−0.0012284*** (0.0000401)
Tenure	−0.0032126*** (0.0002513)	−0.0033208*** (0.0002513)	−0.0031436*** (0.0002512)
Popularity	−0.0001598*** (0.0000158)	−0.000152*** (0.0000158)	−0.0001642*** (0.0000158)
Price	No	No	No
Restaurant category	No	No	No
Restaurant FE	Yes	Yes	Yes
Review year FE	Yes	Yes	Yes
Review month FE	Yes	Yes	Yes
/cut-1	−0.6493999 (0.5359998)	−01.026319 (0.5310995)	−0.5857437 (0.5288668)
/cut-2	0.7317343 (0.5359522)	0.3365711 (0.5310413)	0.7892033 (0.5288257)
/cut-3	2.077409*** (0.5359694)	1.634572*** (0.5310389)	2.145956*** (0.5288517)
/cut-4	3.894637*** (0.536013)	3.424235*** (0.5310816)	3.971123*** (0.5288917)
	Model 3.1 (0.95, 0.05)	Model 3.2 (0.99, 0.01)	Model 3.3 (0.90, 0.10)
Observations	185,969	185,969	185,969
Pseudo R^2	0.1634	0.1556	0.1647
LR chi-square	85879.65	81786.61	86539.02
Prob > chi-square	0.0000	0.0000	0.0000
LL	−219833.48	−221880	−219503.8

Table V. Estimation results – robustness check with restaurant fixed effects

consumer has an extreme dining experience or devotes more cognitive effort to writing the review.

- Compared to elite reviewers, non-elite reviewers of an online review platform are more susceptible to the social influence of prior average review ratings.
- The effect of social influence is attenuated by the variance in existing review ratings.

6.2 Theoretical implications

This study contributes to the previous literature in several ways. First, it is one of the few studies in the hospitality and tourism fields to document the bidirectional nature of social influence on electronic word of mouth (eWOM) for experience-oriented products. Online reviewers, who influence others in their decision-making or even serve as opinion leaders, may also be socially influenced. Marketers, online review websites and social media platforms should understand that consumers' online reviews and ratings are not independent or based solely on their consumption experiences; rather, consumers' ratings are socially influenced to some extent by prior reviews from earlier consumers.

Second, this study made an initial attempt to examine the influence of prior reviews on subsequent review ratings of the same restaurant for consumers with heterogeneous dining experiences and with different online status (i.e. elite vs non-elite) on an online review website. This conclusion extends previous studies on social influence and online review ratings in which heterogeneous consumer consumption experiences and online status were not considered.

Third, to the best of the authors' knowledge, this study is the first to examine the moderating role of review characteristics using a text mining approach. A new variable reflecting a reviewer's cognitive effort in writing a review was considered by counting all cognitive-related words, a technique that first appeared in psychological studies applying language as a significant indicator of cognitive effort. The present work also complements a study from Ma *et al.* (2013) investigating the moderating effect of review length.

6.3 Managerial implications

The findings of this study yield the following important managerial implications for industry practitioners. The restaurant industry and online review platforms would benefit from a clearer understanding of key factors that can decrease social influence to ensure accurate product evaluations.

First, the empirical findings provide valuable insight for the designers of online review platforms. Such platforms can construct indices related to the factors specified in this study to rank the reliability of reviewers and their reviews. Using this type of ranking system would encourage reviewers to invest more cognitive effort in drafting comprehensive and objective reviews, while also filtering out biases to ensure accurate reflections of their consumption experiences. These measures would benefit the third-party online review platforms in the long term.

Second, online review platforms should use filtering techniques for more unbiased eWOM. These platforms can also develop algorithms to recommend reviews free from social influence for each business. Highlighting such reviews and placing them in more prominent webpage locations could help consumers make better purchase decisions. Online review platforms could also post a warning if a review appears to be strongly biased or socially influenced.

Third, reviews and their corresponding ratings are not equally accurate or bias-free. For example, the present study found systematic differences between elite and non-elite reviewers in terms of their online review-rating behavior. Compared to non-elite reviewers, ratings posted by elite reviewers were more resistant to social influence; therefore, online reviews written by elite reviewers were more likely accurately depict their real-consumption experiences. If the ultimate goal of an online reputation system is to provide unbiased reflections of product quality, to fully benefit from consumers' collective wisdom, system designers should assign more weight to review ratings provided by elite reviewers and discount those from non-elite reviewers.

6.4 Limitations and future research

This study is subject to several limitations and raises a few interesting questions that warrant further exploration. First, this research model did not consider the potential influence of cultural background or cultural distance. For example, are Chinese tourists more likely to be socially influenced by prior restaurant reviews written by Chinese? It would be a promising topic in the future to test the role of cultural background and cultural distance, and use profile photos and names of reviewers to identify and measure such type of variables. Second, this study assumed that the social influence of consumers' online review ratings was not affected by the technologies used to read and post online reviews. Webpage designs and consumers' reading habits vary on smartphones/tablets vs personal computers; therefore, future studies could test the moderating effect of reviewers' technologies on their review ratings. Third, although modeling with online secondary data was common in prior research, the social influence of online reviews is difficult to establish using this approach without experimental design. Correlations between earlier and later reviews could be attributable to several reasons, such as the interface on which consumers write online reviews. Therefore, an experimental design should be used to provide additional insights into a true causality effect.

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Appendix 1. Review sentiment calculation

Review sentiment was calculated based on textual reviews. Sentiment analysis in this study aims to classify product/service textual reviews into positive or negative opinions (Calheiros *et al.*, 2017). Scholars recently have used a naïve Bayesian algorithm (Li *et al.*, 2017), lexicon-based approaches (Calheiros *et al.*, 2017) and machine-learning methods (e.g. support vector machine classifiers) (Ganu *et al.*, 2013), to calculate review sentiment.

To ensure analyzable data, we cleaned the text for noise by removing unwanted URLs and HTML tags. The naïve Bayes classifier (McCallum and Nigam, 1998) was used to calculate each review sentiment. The premise of using the joint probabilities of words and categories is to estimate the probabilities of categories in a given document. We adopted the bag-of-words (BoW) method to represent a review document. A BoW is a collection of words that represents a document based on word count, mostly disregarding the order in which words appear. We then developed a vocabulary corpus of all unique words occurring in all documents in the training set. For our purposes, a document represented a vector $dj = (x_{i1}, \ldots, x_{i|V|})$ of word frequencies, where V denotes the size of the vocabulary corpus (*vol*) across all documents; in this study, $vol = (w_1, \ldots, w_{|V|})$. Each $x_{it} = \{0,1,2, \ldots\}$ reflects how often w_t occurs in d_i. Given model parameters $p(w_t | c_j)$ and class prior probabilities $p(c_j)$ with assumed independence of vocabulary terms, the most likely class for document d_i is derived from the following formula:

$$c^*(d_i) = arg\max_j p(c_j) \prod_{t=1}^{|V|} p\left(w_t \;|c_j\right)^{n(w_t,d_i)} \tag{1}$$

where $p(c_j) = \frac{|c_j|}{\sum_{r=1}^{|C|} |c_r|}$, $n(w_t, d_i)$ denotes the frequency of w_t in d_i, and $p(w_t | c_j)$ is estimated from training documents with a known category based on maximum likelihood estimation with a Laplacean prior:

$$p\left(w_t \;|c_j\right) = \frac{1 + \sum_{d_i \epsilon c_j} n(w_t, d_i)}{|V| + \sum_{t=1}^{|V|} \sum_{d_i \epsilon c_j} n(w_t, d_i)} \tag{2}$$

To generate training reviews, two native English speakers were hired as judges to label textual reviews. These judges assigned each review a categorization tag and a degree of uncertainty ranging from 1 to 3, with 3 indicating the greatest uncertainty. We removed a review if the judges could not reach a consensus on its category or if either judge assigned the review an uncertainty degree of 3. Ultimately, we got medium-sized data set, consisting of 1,500 positive and 1,500 negative reviews; 1,000 positive and 1,000 negative reviews constituted the training set, and the remaining 500 positive and 500 negative reviews were in the test set.

K-fold cross-validation was used to determine the performance of the naïve Bayes classifier. The value of K depends on the size of the data set; if the training/test set is large, then we choose a higher K value; a lower value is selected otherwise. According to previous research on naïve Bayes sentiment calculation (Pang *et al.*, 2002), we set K = 3 to ensure sufficient data for testing (500 positive and 500 negative reviews per testing round).

Three-fold cross-validation was conducted by dividing the data set into three subsets, where one subset was used as the test set per round and the other two subsets comprised the training set. After running three iterations of this holdout method, we calculated the average accuracy level: 79 per cent for the naïve Bayes classifier in general and 78/80 per cent and 80/79 per cent for the recall of positive/negative reviews and precision of positive/negative reviews, respectively.

The above metrics show that our sentiment classification using the naïve Bayes classifier was acceptable compared to earlier studies (e.g. Ganu *et al.*, 2013). Therefore, we estimated the parameters of equation (1) based on the entire training and test data sets. We then calculated the review sentiment of the whole data set along with each textual review d_i's probability of being positive $p(c_{pos} | d_i)$ or negative $p(c_{neg} | d_i)$. $\frac{p\left(c_{pos} \;|d_i\right)}{p\left(c_{pos} \;|d_i\right) + \;\; p\left(c_{neg} \;|d_i\right)}$ is the review sentiment value ranging from 0 to 1.

Appendix 2. Examples of extreme positive and negative dining experience (real reviews on yelp)

Extreme positive dining experience (sentiment = 1)

We had dinner here on 12/17/11 .Steak Lovers Heaven! !! If you love steaks this is the restaurant to come while in Vegas. It is pricey but worth every penny. Nice cocktail menu. creative mixologists at work [. . .] I had the asian pear martini and my hubby the traditional ketel one martini a little dirty. for appetizer the pork belly is a must try. it is cruchy on the outside and buttery tender in the inside.perfection. the butter lettuce salad it's amazing. if you can believe that a salad can be amazing you should try this one. With an array of choices from the meat menu could be quite intimidating but the servers are highly trained to help you make the best selection. I chose the bone in petit filet mignon and my hubby tried the kobe filet both charred to perfection on the outside and buttery in the inside. melts in your mouth. WOW! !! worth every penny. for sides we had the brussel sprouts and the spinach both excellent and for dessert the fig cake with gianduja ice cream YUM! Please do not let the name Wolfgang puck confuse you . this one is one of his best restaurants. way different to Spago.

Extreme negative dining experience (sentiment = 9.74973392e − 16)

Worst customer service ever [. . .] It wasn't that busy. We ordered the all you can eat sushi [. . .] but they never came back to the table. They seemed very disorganized. One waiter took our order and then I guess he thought that it wasn't his table anymore. The manager finally helped us after we were there for an hour. They took our order for the next two plates and brought us the wrong food. Then after that they brought us the right food and we didn't eat the wrong order. The waiter said that we have to pay for the food that wasn't consumed even though they made a mistake. They brought us someone Else's bill with a credit card in it. We told him about his mistake and he brought the bill to the right customer. Finally we got our bill, we paid and was about to leave and one of the waiters got physical with us and told us that we must pay for another meal because we were wasting the food. So that is my story of the worst sushi experience that I've ever had. Stay away from this place.

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