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Does certainty tone matter? Effects of review certainty, reviewer characteristics, and organizational niche width on review usefulness

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ABSTRACT

Given the proliferation of online review websites—e.g., Yelp.com—that prominently display a large number of online custome0r reviews, scholars have made efforts to investigate what makes a review "useful." However, there is little research that offers insight into how review content, reviewer characteristics, and review contexts jointly influence review usefulness. We specially examine the role of review certainty on review usefulness. Drawing on dual-process and social influence theories, we examine the interaction effects of review certainty, reviewer popularity, reviewer expertise, and the niche width of a restaurant on review usefulness. In particular, this study focuses on how review certainty interacts with other contextual factors to influence users' evaluation of the usefulness of online reviews. Utilizing a zero-inflated negative binomial Poisson regression, we empirically tested our hypotheses based on 10,097 reviews on 2,383 restaurants from Yelp.com. Our results indicated that (1) the impact of review certainty on review usefulness decreases with reviewer popularity but does not vary with reviewer expertise and (2) the niche width of a restaurant—as a contextual feature—interacts with review certainty and reviewer characteristics in influencing review usefulness. Theoretically, these findings contribute to online customer review literature and certainty literature, as well as social media research, provide new guidelines for predicting review usefulness, and add new insights into understanding the role of organizational positioning for customer evaluations. In practice, our findings can help online review platforms better understand how to screen and select useful reviews for visitors.

1. Introduction

The contemporary proliferation of online communications through social media has facilitated the generation of a vast number of customer reviews for a wide range of products and services online. As one form of electronic word-of-mouth (e-WOM), online customer reviews, which refer to informational communications among customers concerning the evaluations of goods and services, have played an increasingly important role in electronic commerce along several lines, including informing potential customers of product knowledge [40, 52, 59], reducing uncertainty of product quality [61], and increasing product sales [13, 69]. However, completely comprehending large numbers of online customer reviews is a challenging task; hence, the increasing availability of online reviews can cause consumers to experience information overload [29]. Moreover, customers generally consider only a small number of reviews that are especially useful for their own decision-making. [11] corroborate that reviews with a high proportion of helpful votes were perceived as high quality—leading to increased product sales. Accordingly, designing a mechanism to identify useful reviews is a critically important venture for practitioners. In response to the problem of information overload and to answer to the call for identifying useful reviews, social media platforms, such as Yelp.com, provide a peer voting system that asks "Was this review …?" about each review, inviting users to vote each review as "useful," "helpful," or "funny." Although this system can identify useful reviews in an ex post manner, the accumulation of "useful" votes requires time and can delay customer access to useful reviews. An ex ante approach that could *predict* review usefulness could help social media platforms screen and select likely useful reviews that could be immediately delivered to online visitors with limited time and cognitive resources. Our paper intends to offer such an approach that could be used to predict useful reviews based on review characteristics.

At present, product descriptions and slogans generated by sellers frequently use certainty words (e.g., absolutely, must, and always) to persuade potential customers to buy their products or services. Likewise, people also hold opinions with varying degrees of conviction or certainty. For instance, diners writing reviews on a new restaurant may

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differ in *certainty tone*, that is, some may be quite sure of their favorable recommendations—indicated by the use of certain words such as definitely, completely, absolute, etc.—while other, who are not as convinced may fail to use such language. This phenomenon is very prevalent in online review platforms, and examples are shown in Appendix A, where the review certainty[1] is mainly expressed by certain words such as everything, definitely, all, etc. In addition to the nearly ubiquitous existence of certainty tone (e.g., certain, completely, absolutely, sure) in online communications, especially product reviews, certainty tone also affects persuasiveness, as discussed in current behavioral literature (e.g., [31, 63]). These studies mostly focus on the effects of attitude certainty on persuasion by either relying on self--reports—i.e., how certain/convinced are you of your attitude? Or manipulating degrees of certainty in lab-controlled experiments. Although these studies contribute to identifying the impact of certainty on persuasion, they mostly provide a subjective sense of certainty, rather than an objective measurement in a field study. In our research, we utilize a field dataset from Yelp.com to test how different levels of certainty embedded in reviews influence persuasion, which we expect will strengthen the validity and generalizability of the certainty effect.

When exploiting persuasion, source credibility has been the subject of longstanding interest and much attention (e.g., [66]). In particular, the source of a certain message can be deemed credible if the source is either an expert who is perceived as a professional with high levels of ability/knowledge or a popular person with sufficient fame to ensure trustworthiness. Although the incremental effect of source credibility on the persuasiveness of a message has been repeatedly studied [5, 19, 46], the further differentiation between the source-expertise effect and source-popularity effect on the persuasiveness of messages is not well examined. More importantly for our purposes, expertise and popularity define two different types of reviewer features. Expertise highlights a reviewer's rich experience and professional knowledge, while popularity emphasizes a reviewer's social networks. People perceive the certainty tone by an expert as persuasive, while being less persuaded by the certainty tone of a popular person. Thus, to clarify this question, in this study we examine two reviewer characteristics—i.e., expertise and popularity.

Another important characteristic of reviews for our purposes is organization categorization. Customers often rely on categorization to identify and interpret the products or services provided by the organization. An organization can shape its identity by positioning itself within one or more existing specific categories, thus defining the organization's "niche width" [35]. Yelp users tend to perceive an organization with a wide niche that spans multiple categories as having an ambiguous identity and a broad positioning, while they perceive an organization with a narrow niche that concentrates on one specific category as having an explicit identity and a unique positioning—i.e., having authenticity [25]. Organizational niche width can make it easier to understand a business and can moderate the ease and motivation with which users engage in reviews, thus affecting the perceived usefulness of reviews.

Existing research on review usefulness/helpfulness mostly focuses on its determinants, including review characteristics (e.g., emotions; [70]) and reviewer characteristics (e.g., self-identity disclosure; [19]). Although these studies contribute to the understanding of review helpfulness, only limited information is known about the joint effects of review and reviewer features. Furthermore, these studies primarily examine the role of product categorization (e.g., search vs. experience; [42]), while scant attention has been paid to examining the contextual factors from the perspective of an organization's positioning. Finally, most of these studies operationalize review usefulness/helpfulness as a percentage of useful/helpful votes to the total number of votes (e.g., [22, 42, 60, 70]). However, these studies using the percentage-based approach leave out reviews without votes. Yet many online reviews have never received a single vote [9]. Investigating the factors that predict zero-vote situations by focusing directly on the number of usefulness votes is important [68]. Moreover, compared to percentage numbers, the count of helpfulness/usefulness votes is readily visible and supposed to be a direct signal perceived by consumers. Thus, we utilize the ZINB Poisson regression to directly model the count of usefulness votes and estimate both the probability of reviews receiving zero votes and the conditional probability of receiving a certain number of votes. Our approach facilitates the understanding of why different reviews receive zero or a certain number of usefulness votes and thus is of direct interest to social and behavioral scientists [9]. In any case, methods of predicting review usefulness presented in existing studies have yet to be well implemented. For example, to predict the count with a mean of less than 10, certain studies (see, e.g., [54]) adopt a linear regression method that may create biased standard errors for significance tests [21]. Furthermore, some studies have failed to correlate review characteristics with reviewer features (see, e.g., [68]). We seek to improve the predictability of review usefulness and facilitate the eventual implementation of our methods using an appropriate method.

Given the literature gaps identified in the previous paragraphs, our research aims to examine the interaction effects of review certainty, reviewer expertise and popularity, and organizational niche width on review usefulness. First, we focus on the count of usefulness votes and estimate our model using zero-inflated negative binomial (ZINB) Poisson regression, which predicts whether a review will receive a useful vote and how many useful votes will be obtained. Second, based on the existing literature, we add one more review textual feature—certainty—which is the subjective confidence or conviction of the expressed opinion about a product or service. This feature is measured by the frequency of certainty words occurring in a review, such as absolutely, must, always, and definitely. Third, we examine the interaction effects among review certainty, reviewer characteristics, and organizational features. For reviewer features, we examine reviewer expertise and popularity. For organizational features, we primarily consider the niche width of an organization. We integrate dual-process theory with social influence theory to explain our model. Overall, we find that (1) the impact of review certainty on review usefulness decreases with reviewer popularity but does not vary with reviewer expertise; (2) the niche width of a restaurant—as a contextual feature—interacts with review certainty and reviewer characteristics in influencing review usefulness.

Our study provides important contributions to the e-WOM literature and extends dual-process theory. First, our study adds insights to the fast-growing stream of text mining studies that emphasize the role of textual characteristics in influencing consumer judgment (see, e.g., [35, 43]) by examining the certainty language embedded in textual review content. Second, our findings supplement the review usefulness literature (see, e.g., [19, 42, 70]) by verifying and identifying both the solitary and interaction effects of review certainty, reviewer popularity, expertise, and organizational niche width. Our study also adds to the current literature on review usefulness/helpfulness (see, e.g., [42]) by directly examining the count of useful votes rather than the percentage of useful/helpful votes to the total number of votes using ZINB Poisson regression for estimation. Extant studies mainly use the percentage-based approach to predict review usefulness, leaving out reviews without votes. With the use of the ZINB Poisson model, we can test two-stage models in which the logit and the standard negative binomial (NB) model are estimated jointly. The former estimates the probability of reviews receiving zero useful votes, whereas the latter predicts the conditional number of useful votes. We can then empirically investigate and understand why different reviews receive zero or various usefulness votes. Third, our findings contribute to the certainty literature [14, 56, 58] by identifying three moderators to modify the persuasion effect of certainty from both reviewer and organization perspectives. Fourth, our findings extend dual-process theory by

[1] Review certainty here is a continuous variable that indicates the degree of certainty tone of a review.

determining an additional peripheral cue, reviewer popularity, which has received less attention in dual-process research but is common in the context of social media. Finally, our findings that the joint effects of review certainty and reviewer popularity/expertise on review usefulness differ across organizational niche widths contribute to the body of current research on organizational positioning (see e.g., [17, 35]) and strengthen the understanding of how organizations may proceed in generating and employing useful reviews. Practically, our findings offer actionable implications for managers of online review websites (e.g., Yelp.com) in critical information screening and selection, for online retailers in providing guidelines for customer review writing, and for managers of social media platforms in enhancing the implementation of social media marketing.

2. Literature review

2.1. Review usefulness

Scholars have identified various determinants of review usefulness/ helpfulness (see, e.g., [19, 42, 70]), including contextual attributes, reviewer characteristics, and review textual features. Existing studies mainly examine three key components of an online customer review: review, reviewer, and context.

One stream of studies has examined numeric ratings, finding that negative reviews are more useful in customer decision-making than positive reviews (see, e.g., [13]). For example, [42] identified that for experience goods, reviews with extreme ratings are usually perceived as less helpful than those with moderate ratings. However, the information embedded in reviews cannot be completely captured by numeric ratings [55]. In recent years, scholars have directly investigated review text using text mining techniques. For instance, [34] and [9] evaluate the stylistic characteristics of a text (e.g., readability and word length) on the basis of the review helpfulness ratio. In terms of sentiment characteristics, [70] show that the emotions embedded in a review influence customers' perception of review helpfulness and therefore propose that anxiety-embedded reviews are more helpful than anger-embedded reviews. Moreover, [47] adopt content analysis to capture the embedded innovativeness expressed in reviews and determined a curvilinear relationship between the expressed innovativeness and review helpfulness.

Aside from review textual factors, the characteristics of reviewers, such as reviewer authorship (see, e.g., [19, 22]) and reviewer reputation (see, e.g., [46]), also influence review usefulness/helpfulness. [19] used the disclosure of self-identity information to explain the review helpfulness ratio and determined that such disclosure positively affects the review helpfulness ratio. [22] demonstrated the positive effects of a reviewer's history on the review helpfulness ratio. To investigate review helpfulness on Amazon.com, [46] view the reviewer's reputation in the community as one dimension of review quality and measured it along

Table 1
Summary of relevant studies on review usefulness/helpfulness.

Article	Data	Method	Usefulness/Helpfulness	Review Predictors	Reviewer Predictors	Context Predictors
[42]	Amazon	Tobit regression	Percentage of helpful votes out of total votes	Length Rating extremity	Null	Search vs. experience
[70]	Yahoo!	Tobit regression	Percentage of helpful votes out of total votes	Anxiety Anger	Null	Null
[19]	Amazon	Tobit regression	Percentage of helpful votes out of total votes		Self-identity disclosure	Null
[22]	Amazon	Tobit regression	Percentage of helpful votes out of total votes	Subjectivity Readability Spelling errors	Average helpfulness of reviewer' historical reviews	Null
[34]	Amazon	Tobit regression	Percentage of helpful votes out of total votes	Length Readability	Null	Null
[46]	Amazon	Simple linear regression	Percentage of helpful votes out of total votes	Topical relevancy Ease of understanding Believability Objectivity	Reviewer's reputation	Null
[60]	E-retailer website	OLS	Percentage of helpful votes out of total votes	Rating valence	Null	Hedonic vs. utilitarian
[47]	Amazon	Logistic regression	Percentage of helpful votes out of total votes	Valence Age Length	Reviewer expressed innovativeness	Utilitarian vs. experience
[38]	IMDB	Nonlinear regression	Percentage of helpful votes out of total votes	Writing style Timeliness	Reviewer expressed expertise	Null
[5]	Amazon	Hierarchical regression	Percentage of helpful votes out of total votes	Length Percentage of negative words to total word count	Rating inconsistency Reviewer ranking Reviewer real name	Search vs. experience High-priced vs. low-priced
[9]	CNETD	Ordinal logistic regression	Number of helpfulness votes	Basic, stylistic and semantic characteristics	Null	Null
[54]	Yelp	OLS	Number of usefulness votes	Elaborateness Valence	Self-identity disclosure Expertise Reputation	Search, experience vs. credence service
[68]	Yelp	ZINB Poisson regression	Number of usefulness votes	Length Ease of understanding	Network centrality Elite badge	Null
[45]	Yelp & Amazon	Hybrid text regression	Number of usefulness votes	Vector space model of review text	Reviewer engagement	Null
[71]	Amazon	Binary logit model	Likelihood of helpfulness	Star rating	Null	Promotion vs. prevention goal
[26]	Null	Tobit Regression	Percentage of helpful votes out of total votes	Product rating Word count	Reviewer Experience Reviewer Impact Cumulative helpfulness	Null
[30].	Google Play	Heteroscedasticity-consistent regression	Helpfulness ranking	Depth/length Rating valence Equivocality	Profile image/image type	Null
[62]	Amazon.com	Tobit regression	Percentage of helpful votes out of total votes	Product quality relatedness Strength of review sentiment Review uncertainty	Reviewer expertise Reviewer non-anonymity	Experience vs. search goods

more than five metrics, such as the number of previous helpfulness votes received, number of total reviews written, and the "top reviewer" badge.

With regard to contextual factors, previous studies have mostly focused on product characteristics. For example, [42] focus on the moderating role of search versus experience goods in the impact of rating extremity on review helpfulness. Sen & Lerman [60] examined the moderating role of utilitarian versus hedonic products in the relationship between review valence and review helpfulness, thereby suggesting that negative hedonic product reviews are less useful than those of utilitarian products.

Table 1 lists the relevant studies on review usefulness/helpfulness. Although these studies have been instrumental in enhancing our understanding of review usefulness, two interesting issues remain unaddressed. First, According to our literature review, few studies have directly investigated the role of review certainty as a predictor of review usefulness. Further, most existing studies focus on solitary effects; hence, limited information is known about the joint effects of review certainty, reviewer characteristics and organizational characteristics on review usefulness. Moreover, contemporary studies emphasize the moderating role of product characteristics (i.e., search vs. experience), but few have looked into the matter from the perspective of the positioning of an organization (i.e., a generalist or a specialist). To fill this gap in the literature, this study intends to determine the interaction impacts of review certainty, reviewer popularity and expertise, and niche width of an organization on review usefulness. Second, the majority of existing studies measure review helpfulness as the percentage of helpful votes to the total number of votes (see, e.g., [42, 70]), while we directly model the count of helpfulness votes (e.g., [9]), which is supposed to be a direct signal perceived by consumers. Besides, considering that many online reviews on different websites have never received a single vote [9], investigating the factors that predict zero-vote situations by focusing directly on the number of usefulness votes is important [68].

2.2. Certainty

Academic researchers in marketing and organizational behavior have frequently addressed the impacts of review certainty in persuasion. For example, [31] found that nonexperts stimulate involvement and promote persuasion by expressing certainty. Table 2 lists the relevant studies on certainty. Although these studies have been instrumental in understanding the impacts of certainty on persuasion, several interesting issues remain unanswered. First, as shown in Table 2, current studies mostly focus on the effects of attitude certainty on persuasion by either relying on self-reports—i.e., how certain/convinced are you of your attitude?—or by manipulating degrees of certainty in lab-controlled experiments (e.g., [14, 56, 58]); few studies use field studies to provide objective measurements of certainty. Second, there are mixed findings regarding the impacts of certainty on persuasion. For example, [14] suggest that when controlling for valence and extremity, the opinions held with certainty are less conducive to systematic processing than those held with uncertainty. [70] demonstrate that the anger characterized by certainty induces reliance on peripheral cues, whereas anxious reviewers appraised as uncertain tend to engage in effortful processing. On the basis of these papers then, certainty should negatively affect review usefulness by inducing a lack of engagement in users evaluating certain types of messages. However, [63] specify that, compared with advisors expressing low certainty, those with high certainty are more trusted and their advice tends to be better accepted. These mixed findings suggest that while certainty sometimes negatively influences persuasion, this is not always the case. To attempt to clarify this inconsistency in the literature, we utilize a field dataset from Yelp.com to test how different levels of certainty embedded in reviews influence persuasion, which we expect will strengthen the validity and generalizability of the effects of certainty on persuasion. Moreover, we identify three moderators that modify the effect of certainty on review usefulness from both reviewer and organizational perspectives.

Table 2
Summary of relevant studies on certainty.

Article	Focus	Key Findings	Method
[14]	Attitude certainty	Attitude certainty positively influences univalent attitude but negatively affects ambivalent attitude.	Laboratory experiments
[49]	Attitude certainty	With the increase of attitude certainty, people hold attitudes more resistant to counter attitudinal messages.	Laboratory experiments
[58]	Attitude certainty	Different writing styles induce attitudes with either high or low certainty.	Laboratory experiments
[66]	Attitude certainty	Attitude certainty is higher for a message from a source with high expertise versus a source with low expertise.	Laboratory experiments
[31]	Source certainty	Low expertise sources promote persuasion when they express certainty, whereas high expertise sources promote persuasion when they express uncertainty.	Laboratory experiments
[56]	Attitude certainty	People had higher attitude certainty when following failed counterarguing compared with following undirected thinking.	Laboratory experiments
[65]	Emotional certainty	Emotional certainty promotes heuristic processing, whereas emotional uncertainty leads to systematic processing.	Laboratory experiments
[14]	Attitude certainty	Attitude certainty amplifies the dominant effect of the attitude on thought, judgment, and behavior.	Laboratory experiments
[63]	Confidence	High confidence by advisors positively influenced judges' tendency to follow their advice.	Laboratory experiments
[67]	Attitude certainty	Review the antecedents, consequences and new directions of attitude certainty in the existing research.	Review
[57]	Attitude certainty	Propose a framework of appraisal-based attitude certainty from past models in attitudes and persuasion research.	Review
[39]	Attitude certainty	Focusing on feelings (vs. deliberation) in choice can lead to enhanced attitude certainty.	Laboratory experiments
[16]	Attitude certainty	Demonstrate dispositional variability in attitude certainty.	Survey

3. Theoretical foundation and model

For this study, we selected dual-process and social influence theories jointly as our theoretical foundation for the following reasons: First, we use dual-process theory to illustrate the interaction between the content and source of reviews and to articulate the shift between systematic processing and heuristic processing based on the strength of the elaboration likelihood (i.e., how likely a user is to engage with a message). By contrast, social influence theory goes deeply into the source effect and mainly explains two forms of social influence enforced by two characteristics of the source—i.e., expertise and popularity. Given our research objective of examining the joint effect of review content and reviewer characteristics on persuasion, it is reasonable to consider both dual-process theory and social influence theory for this study.

Second, the combination of these two theories builds our theoretical foundation. On one hand, informational influence is activated through the internalization of information into one's own belief knowledge base and beliefs, and this internalization process is highly involved with the systematic processing of a message, which depends on the message's elaboration likelihood. On the other hand, normative influence is enabled by the identification process, which primarily leads to blind following without effortful evaluation. We also argue that the niche width of a reviewed organization may influence people's elaboration likelihood, because the niche width reflects the organization's identity, which review recipients use as reference a reference point.

3.1. Dual-process theory

Dual-process theory hypothesizes that multiple factors influence the extent to which people think about aspects of intercommunications, including features of sources, recipients, and messages [50]. Dual-process theory has been developed and applied to persuasion literature, e.g., in the heuristic-systematic model by [10] and the elaboration likelihood model by [50]. These theories indicate that when people are highly motivated and can assess messages, they tend to devote great effort to engage with such messages through systematic processing, so that persuasion largely depends on message content—this is known as the central route of processing, also called systematic processing. During systematic processing, message recipients scrutinize the presented information and incorporate it into what they already know. When engagement with a message decreases, peripheral cues, such as source credibility, become increasingly important in persuasion—which is known as the peripheral route of processing, also called heuristic processing. During heuristic processing, message recipients use heuristic and simple decision rules embedded in the message context. Systematic and heuristic processing can both result in positive validity assessments but are not necessarily automatic. Systematic processing requires motivation, ability, and sufficient cognitive resources, and it is limited if people choose not to make sense of messages or are not mentally capable of making sense of them. Similarly, heuristic processing depends on the availability of cues and awareness of the heuristic factor associated with these cues. When conditions for systematic and heuristic processing are met, both processing modes can occur concurrently. For instance, people who are about to purchase a product may read product-relevant information presented in a product review. If this information is perceived as persuasive, then it leads to favorable attitudes, which may include purchase intentions; otherwise, it will lead to unfavorable attitudes. This type of processing aligns with systematic processing via the central route. People may also focus on the attractiveness, credibility, or prestige of product endorsers, which aligns with heuristic processing via the peripheral route.

The empirical studies that apply dual-process theory primarily examine the factors that explain message quality or source credibility [4]. In general, source credibility can enhance the persuasiveness of a message (e.g., [53]). Most studies of source credibility focus on source expertise and emphasize the perceived ability of the source to provide useful viewpoints [4]. In addition to source expertise, we also examine the effects of source popularity, an additional peripheral cue that has received less attention in dual-process research, but is commonly found in the context of social media.

3.2. Social influence theory

[33] indicates that social influence operates through three distinct processes—namely, compliance, identification, and internalization. Internalization occurs when people accept others' opinions and integrate them into their own belief systems. Compliance occurs when people publicly conform to others' opinions. Identification arises when people adopt others' opinions or behaviors to establish a relationship with a group. These processes can relate to two forms of social influence proposed by [7]: informational and normative influences. Normative and informational influences reflect individuals' perception of others' behavioral influence. Observed behaviors, or those that can be regarded as information (e.g., high-quality signals) to help make decisions, are called informational influence. Meanwhile, observed behaviors can be perceived as normative pressure—that is, decision-making is not owed to the information obtained by observation but through normative pressure called normative influence. Informational influence pertains to the influence to accept information obtained from another as evidence about reality. Hence, such influence induces the acceptance of information corresponding to internalization process. Informational influence is then accepted because of internalization, as it is instrumental to the goal. Information can be internalized if it enhances individuals' knowledge about their environment or ability to cope with problems. Research has suggested that internalization is caused by increased cognitive activity or message processing (e.g., [36, 41]). [64] suggest that if individuals acquire more information than others, they possess greater confidence to guide later behavior or attitude formation.

By contrast, normative influence is the tendency to conform to the expectations of others that can be attributed to either compliance or identification. If individuals are motivated to enhance their self-concept, then they are expected to accept the influence of referents by associating themselves with positive referents or dissociating from negative referents, which is called the identification process. Individuals identify themselves by adopting behaviors or opinions that they perceive as representative of their reference groups. Hence, individuals perform certain behaviors or adopt beliefs due to their enhancing or supporting effect on individuals' self-concept and the reward inherent in this enhancement or support. Thus, individuals adopting messages through a source are recipients who can enhance their self-esteem by identifying with the source.

In this study, we use social influence theory to argue that reviewers' expertise influence and popularity influence initiate the internalization and identification processes, respectively. Thus, informational influence emphasizes the internalization process activated by the signals of rich knowledge and experience, which can be perceived as expertise. By contrast, normative influence highlights the identification mechanism invoked by reviewers' social networks, which can reflect their popularity.

3.3. Research model

To examine review usefulness, we integrate dual-process theory with social influence theory to explain the underlying rationales behind our research model (Fig. 1). As shown in Fig. 1, we illustrate four factors that predict review usefulness—namely, review certainty, reviewer expertise, reviewer popularity, and organization niche width. We argue that the effect of review certainty on review usefulness is moderated by reviewer characteristics—in particular, reviewer expertise and reviewer popularity—and that based on these, review certainty has different outcomes in terms of how much effort a recipient devotes to internalizing a review. We define a reviewer with many followers as a popular reviewer and a reviewer who has written many reviews as an expert. Since a reviewer who writes high-quality reviews is more likely to capture users' attention and to be followed, reviewer popularity may

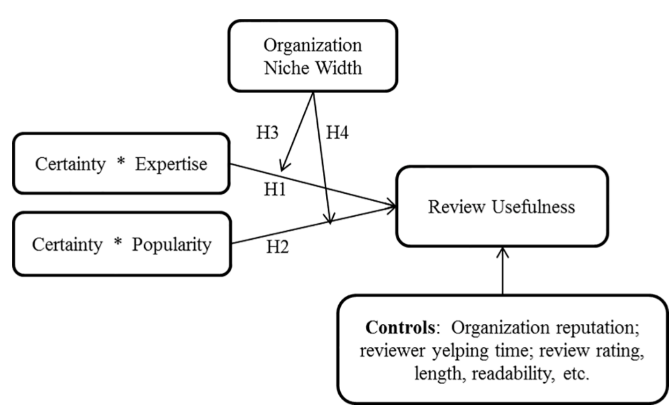


Fig. 1. Research Model. *Note:* * indicates the interaction effect between certainty and expertise and the interaction effect between certainty and popularity.

also reflect reviewer expertise to some extent.

In the current study, however, we treat popularity and expertise as two distinctive variables for the following reasons. First, popular reviewers may be well known for reasons other than expertise. Thus, their reviews may or may not be rich in terms of information and valuable experience. Moreover, having many fans may attract more followers, thus leading to a herding effect. Second, on Yelp.com, people can directly detect Facebook friends and follow them. If a reviewer has many Facebook Friends to draw Yelp followers from, he/she may have a high popularity on Yelp with little expertise on food or restaurants. Thus, a popular reviewer is not necessarily one with expertise. Second and more important, popularity and expertise represent two different kinds of social influence. The former refers to normative social influence while the latter is aligned with informational influence. Normative influence highlights the identification mechanisms associated with a reviewer's social networks, while informational influence emphasizes the internalization process activated by the signals of rich knowledge and experience. We thus postulate that the mindless processing of certainty content is more associated with popularity than expertise.

We also consider the niche width of an organization and examine its moderation effects. Niche width describes the number of different categories an organization spans and is applicable to other contexts as well. As suggested by [35], an organization can shape its identity by positioning itself within existing specific categories. An organization with a narrow niche serves a small percentage of the market, caters to specialized demands, and is often regarded as a specialist. By contrast, an organization with a wide niche serves a large percentage of the market, caters to various demands, and is often regarded as a generalist. For example, a beauty services business that not only offers haircuts, but also makeup for special occasions would be considered a generalist. In contrast, if such a business focuses only on hair-related services, it would be considered a specialist. Customers often rely on categorizations as a means of identifying and interpreting the products or services provided by the organization. Therefore, we argue that organizational niche width may correlate with the ease with which a recipient engages with reviews. These predictors and relationships are explained in detail in the subsequent section.

4. Hypotheses development

4.1. Review certainty

On online customer review websites (e.g., Yelp.com), customers can express their satisfaction (positive opinions) or dissatisfaction (negative opinions) regarding a product or service. Regardless of whether they are satisfied or dissatisfied, customer opinions may also vary in terms of confidence or ambiguity, a dimension which has been conceptualized as *attitude certainty* [1]. In contrast to consumer behavior and social psychology research, in which attitude certainty is measured by asking the question "How certain/convinced are you of your attitude?" [56], the present study directly captures the confidence of a reviewer's opinion by calculating the frequency with which certainty words occur in a review—such as must, absolutely, completely, and definitely. In this study, we identify three moderators to modify the effect of certainty on review usefulness from both reviewer and organization perspectives. We focus on reviewer expertise and popularity as reviewer characteristics, and we examine the niche width of an organization as one organizational feature.

4.2. Review certainty and reviewer expertise

Expertise is characterized as "an actor's ability to provide information to others because of his or her experience, education, or competence" [6]. Here, reviewer expertise is measured by the number of previous reviews written. Expert reviewers are those who are write and post many reviews on Yelp.com, thereby accumulating knowledge about certain product categories. By contrast, nonexpert reviewers post few reviews and, hence, deliver little knowledge to customers by reviewing products or services. We expect a positive impact of reviewer expertise on review usefulness. Here our interest is in how reviewer expertise moderates the effect of review certainty on review usefulness.

When the reviewer is an expert who has written many reviews, social influence occurs through internalization. Internalization occurs when an expert's opinions appear useful for solving a particular problem. A wealth of review-writing experience may be taken as a signal for the cognitive effort necessary to generate a quality review of high degree of certainty [8, 32]. In this case, the recipients of a review believe that a reviewer with rich review-writing experience and relative knowledge is willing to spend effort to provide evaluations and ensure recommendation certainty [23, 51]. In other words, reviewer expertise may increase recipients' perceptions of the reviewer's cognitive efforts,[2] which is supposed to be associated with high-quality arguments [18, 51] and reduction of uncertainty [20, 37]. As dual-process theory suggests, recipients are increasingly engaged to carefully think about the high-quality arguments [50], and this careful processing may drive a well-articulated attitude with a positive affect that signals the successful resolution and usefulness of the relevant recommendation [20].

H1: Reviewer expertise positively moderates the effect of review certainty on the usefulness of a review such that the higher the expertise, the greater impact of certainty on review usefulness.[3]

4.3. Review certainty and reviewer popularity

Popular reviewers are followed by a many people, whereas unpopular ones are followed by few people. Many factors may be responsible for attracting followers, including an already robust online presence, having a lot of followers, rich background knowledge, humorous writing style, and even a pleasantly expressed dining experience. In other words, as already discussed above, popular reviewers do not necessarily have expertise. In this paper, we concentrate on the effects of being a popular reviewer—particularly on how having a significant number of followers affects review persuasion. We expect reviewer popularity to have a positive effect on review usefulness. In this study, we focus on how the role of reviewer popularity moderates the effect of certainty on review usefulness [2].

When an individual is very popular online, social influence occurs mainly via identification. In particular, this occurs when someone attempts to establish or maintain identification with a popular person. Applying identification influence to our context, a review posted by a popular reviewer with hundreds of fans should cause recipients to engage in mindless, heuristic processing requiring minimal direct thought about the message. In other words, when recipients encounter reviews posted by popular reviewers, rather than conducting a careful and effortful evaluation of reviews by internalizing certainty content and evaluating review quality, they may tend to mindlessly follow via identification. Given that the systematic processing of certain points made by reviews requires motivation and sufficient cognitive resources, the persuasiveness of reviews may be limited if recipients make little effort to understand them. We predict that the popularity of reviewers weakens recipients' motivation to engage with reviews and to verify the

[2] We have conducted a summary of relevant studies on cognitive effort as shown in Appendix H.

[3] Conceptually, our hypothesis does not necessarily rely on the assumption that recipients are always checking reviewers' profiles; rather, our rationale is that when a user senses a strong certainty tone in a review—e.g., "Definitely the best Spanish food in town," he or she will tend to look for evidence to support the credibility of this strong opinion from the reviewer. Whether users look at the reviewer's profile is unobservable using our current dataset. We thus acknowledge the limitation and call for future research to tackle this issue.

certainty content of reviews, which leads to less perceived usefulness of high certainty reviews.

H2: Reviewer popularity negatively moderates the effect of review certainty on the usefulness of a review such that the higher the popularity, the weaker impact of certainty on review usefulness.

4.4. Moderating role of organizational niche width

Reviewing a generalist spanning multiple categories is more demanding and effortful than reviewing a specialist who concentrates on one category. This is because customers often rely on categorization to identify and interpret an organization's products or services. A business can shape its identity by positioning itself within existing specific categories, thus defining its "niche width" [35]. For example, restaurants offering multiple cuisines (e.g., serving both Chinese dishes and Japan sushi) often have more complex features than restaurants offering a single kind of food (e.g., that only serve hamburgers; [35]). We argue that it is cognitively more demanding to review a generalist than a specialist because of the generalists' ambiguous identity and the broad positioning. This can contribute to review recipients being less motivated to thoroughly evaluate the review. That is, the more diversified the categories of an organization are, the less motivation recipients will have to absorb and digest reviews on the organization. This, in turn, can inhibit recipients from internalizing reviews into forms of self-belief or persuasion.

As discussed in the lead-up to H1, we posit that reviewer expertise enhances the effect of certainty content on review usefulness via informational influence (as part of the internalization process). Relevance and the ease of understanding motivates people to devote cognitive efforts to systematic processing and knowledge absorption—i.e., the internalization of a strong opinion. However, we anticipate that reviews on broadly positioned organizations—i.e., organizations with greater niche width—will weaken the putative enhancing effect of reviewer expertise due to the difficulty of evaluating the information. Thus, we contend that the effect of expertise will be weakened by greater organizational niche width.

We argue that when an expert reviewer recommends a narrowly positioned organization, recipients can easily understand the reviewer's opinion and transform the information from the review into their own knowledge, thereby increasing their level of understanding. In contrast, if an expert reviewer recommends a broadly positioned organization, the recipient may be less motivated to internalize the review, because, if the reviewer reviews the entire scope of the restaurant, it may be overwhelming and difficult for the recipient to digest, while if the reviewer covers only certain categories, the expert's review may or may not match the recipients' interests [25]. Therefore, we posit that the positive effect of expertise will be negatively moderated by the influence of wide organizational niche on recipient judgments of review usefulness.

H3: There is a negative interaction impact of organizational niche, review certainty, and reviewer expertise on the usefulness of a review such that the high certainty review written by an expert reviewer is more useful for an organization with fewer categories.

As discussed in the lead-up to H2, we posit that reviewer popularity weakens the effect of certainty content on review usefulness via normative influence (as part of the identification process). Identification to a popular reviewer causes recipients to engage in mindless, heuristic processing, and weakens recipients' motivations to evaluate reviews. However, when the target is a generalist, the broad range of food/cuisine categories and their vagueness in terms of authenticity may prevent recipients from simply following popular reviewers to verify certainty content. Instead, reviewers are likely to induce less heuristics but more systematic processing in this case because recipients will be motivated to carefully evaluate certainty content to figure out the specific categories of products reviewed. For example, regarding reviews about restaurants that serve multiple cuisines, including Chinese hot pot, Japanese sushi and American sandwich, recipients tend to be cognitively involved to first determine the category of product(s) with which reviewers are definitely satisfied or dissatisfied and then internalize the digested information as evaluation reference.

On the contrary, for reviews of narrowly positioned organizations (e.g., restaurants that only serve Chinese hot pot), we posit that the ease of understanding the information makes recipients less motivated to conduct effortful evaluation but more likely to rely on the popularity of reviewers via the identification process. That is, for narrowly positioned organizations, recipients tend to simply follow popular reviewers without carefully reading and considering the certainty content, leading to less perceived usefulness of high certainty reviews. Therefore, we contend that the negative moderating effect of reviewer popularity will be weakened by organizational niche width, leading to a positive three-way interaction in H4.

H4: There is a positive three-way interaction of organizational niche, review certainty, and reviewer popularity on the usefulness of a review such that high certainty reviews written by popular reviewers are more useful for organizations that span more categories.

5. Data

5.1. Data collection

Our research context is Yelp.com, a popular online review website founded in October 2004. Yelp covers a broad range of 22 product and service categories, such as restaurants, shopping, beauty, and spas, each of which contain subcategories. For example, the "restaurants" category includes 75 subcategories, such as Chinese, Japanese, Pizza, and Sandwiches. Some restaurants belong to a single subcategory, whereas others occupy multiple subcategories. This categorization is accomplished by the Yelp website, sometimes in consultation with individual restaurants. In addition, the Yelp interface provides information about reviewers to help review recipients quickly evaluate reviewers and their reviews. Below each reviewer's name and registered city are the number of reviews and the number of friends the reviewer has; these elements indicate how heavily the reviewer is involved with the Yelp website. By responding to a review, users become a fan or friend of the reviewer. The key difference between friends and fans is that friends have visible profiles, while fans are anonymous. On Yelp, anyone (with or without an account) can read a written and published review and respond to it as "useful," "funny," or "cool."

We employed the Yelp Academic Data Set released on January 2014 to establish our own research sample using SAS software. We selected restaurants as the target research object, because a restaurant is a typical experience good, the quality of which cannot be thoroughly inspected before purchase. We selected only restaurants with active listings on Yelp as of January 2014, because Yelp includes only restaurants that are operational at the time of searching and viewing. We focused only on reviews published during three months before the dataset release date—that is between October 2013 and December 2013.

Concerning the research time window, we choose a three-month period for the following reasons: Reviewer characteristics essentially refer to (1) expertise—i.e., the number of reviews that reviewers have previously written and (2) popularity—i.e., the number of fans that reviewers had at the time of data collection. Since a reviewer can write more reviews and attract more fans over time, reviewer characteristics can change over time. The Yelp dataset provides values related to the above two variables and our focal dependent variable—i.e., number of usefulness votes a review had received at the time of data collection (Jan 2014). We presume that there would be no significant changes in reviewer characteristics during such a relatively short, three-month

Table 3
Measurement of variables.

Variable type	Variable Name	Measures
Dependent variable	Review usefulness	Number of usefulness votes
Independent variables	Review certainty	(Certainty-related words/total words in a review)*100
	Reviewer expertise	Number of previous reviews written by a reviewer
	Reviewer popularity	Number of fans of a reviewer
	Restaurant niche width	Number of cuisines a restaurant offers
Control variables	Rating	Number of stars given by a reviewer in his/her review of the restaurant
	Length	Number of words in a review
	Readability	Gunning fog index=0.4*(average words per sentence+ count of hard word for each 100 words), where a "hard" word here is defined as a word with more than six characters. *Note*: the larger the readability, the harder it to read the review.
	Anger	(Anger-related words/total words in a review)*100
	Anxiety	(Anxiety-related words/total words in a review)*100
	Positivity	(Positive emotion-related words/total words in a review)*100
	Negativity	(Negative emotion-related words/total words in a review)*100
	Review age (weeks)	Number of weeks elapsed since a review posted
	Reviewer status	A dummy variable, titled as "elite" or not
	Reviewer Yelp tenure (weeks)	Number of weeks elapsed since a reviewer registered
	Reviewer average rating	Average of all the ratings given by a reviewer in the entire time period of data collection
	Restaurant price	Price level ranging from $, $$, $$$ to $$$$: "$" ranking denotes "cheap, under$10″; "$$" denotes "moderate, $11–$30″; "$$$" denotes "pricey, $30–$61″; "$$$$" denotes "splurge, above $61."
	Restaurant reputation	Average rating of all the reviews that a restaurant had received in the entire time period of data collection
	Restaurant popularity	Total number of reviews obtained by a restaurant
	Restaurant age (weeks)	Date of data collection minus date of the first review of a restaurant

observational time window. We also test our hypotheses using the dataset drawn from the six-month time window of July 2013–December 2013. The results are shown in Appendix B, showing support for most of our hypotheses.

Finally, we only examine reviews comprising more than 50 words because for texts with less than 50 words, the content analysis obtained from the linguistic inquiry and word count (LIWC) program is of low credibility (http://liwc.wpengine.com/how-it-works/). Thus, our entire sample includes 10,097 reviews written by 6191 reviewers of 2383 restaurants in the U.S. state of Arizona from October 2013 to December 2013. In our research sample, we have 1302 (55%) restaurants offering one type of cuisine, 549 (23%) restaurants offering two types of cuisines, and 532 (22%) restaurants offering three or more cuisine types.

Table 4
Descriptive statistics.

Variables	Mean	Std. Dev.	Min	Max
Review usefulness	0.71	1.64	0.00	48.00
Review certainty	1.60	1.32	0.00	11.43
Reviewer expertise	71.30	162.44	1.00	2110.00
Reviewer popularity	3.30	17.74	0.00	569.00
Restaurant niche width	1.80	0.83	1.00	3.00
Rating	3.76	1.31	1.00	5.00
Length	154.68	101.40	50.00	530.00
Anger	0.25	0.54	0.00	10.94
Anxiety	0.14	0.40	0.00	6.06
Positivity	5.48	2.79	0.00	20.37
Negativity	1.04	1.18	0.00	12.73
Readability	12.71	5.04	3.44	127.74
Review Age	10.78	3.77	4.35	17.32
Reviewer status	0.15	0.35	0.00	1.00
Reviewer Yelp tenure	119.27	84.90	4.35	473.63
Reviewer average rating	3.75	0.79	1.00	5.00
Restaurant reputation	3.79	0.52	1.00	5.00
Restaurant popularity	144.52	165.89	3.00	1124.00
Restaurant age	247.01	134.86	12.12	473.57

5.2. Data preparation

To capture the textual characteristics of the reviews, we conduct content analysis using the LIWC software program [48], the reliability and validity of which has been extensively investigated [48]. This technique has been recently and frequently used in information systems (IS) and marketing research. For example, with the use of LIWC, Humphreys [27] tracked the creation of casino gambling markets by analyzing newspapers and Yin et al. [70] captured the specific emotions "anger" and "anxiety" embedded in reviews.

The LIWC application relies on an internal default dictionary that defines which words should be counted in the target text files. The dictionary is composed of almost 4500 words and word terms, each of which defines one or more word process and category. There are 26 word categories representing linguistic processes with general descriptor categories (e.g., total word count and words per sentence) and standard linguistic dimensions (e.g., percentage of words in the text that are pronouns, articles, and auxiliary verbs); 32 word categories tapping psychological processes that include social processes (e.g., family, friends, and humans), affective processes (positive emotion, negative emotion, anger, anxiety, and sadness), and cognitive processes (e.g., certainty, insight, and causation); seven personal concern categories (e.g., work, home, and leisure activities); three spoken categories (e.g., assents, fillers, and nonfluencies); and 12 punctuation categories (e.g., periods and commas). For the processing of each word, LIWC searches its dictionary for a match, and if a match occurs, the corresponding category scale for that word would be incremented. At the end of this process, a final score is added to each category, representing the percentage of associated words in the text sample matching that category. For example, the word "annoyed" would be assigned to six-word categories: anger, negative emotion, overall affect, ad, verb, and past tense verb. Hence, if this word is found in the target text, each of these six categories' scale scores will be incremented.

In this study, we conduct content analysis on the text of each review entered for each restaurant using LIWC, which calculates the total frequency of the dictionary words that appear in a category divided by the

Table 5
Correlation of variables.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Usefulness	**1**																		
Certainty	−0.01	**1**																	
Expertise	0.33***	.00	**1**																
Popularity	0.35***	−0.00	0.63***	**1**															
Niche width	−0.01	0.01	0.02	0.01	**1**														
Status	0.32***	0.01	0.52***	0.33***	0.01	**1**													
Rating	−0.03**	0.03**	−0.00	0.02	0.02*	0.02*	**1**												
Length	0.02	−0.09***	0.01	0.01	−0.00	0.01	−0.00	**1**											
Anger	0.01	0.01	−0.01	−0.00	−0.01	0.02*	−0.04***	0.03***	**1**										
Anxiety	0.01	−0.00	0.00	0.01	−0.01	0.00	−0.04***	0.02	0.05***	**1**									
Positivity	0.00	0.18***	0.01	0.00	0.04***	0.01	0.10***	−0.28***	−0.13***	−0.10***	**1**								
Negativity	0.01	0.01	−0.01	−0.00	−0.02	0.00	−0.08***	0.02*	0.55***	0.42***	−0.24***	**1**							
Readability	0.00	0.00	−0.00	−0.00	0.01	−0.01	0.01	0.11***	0.02	0.01	−0.05***	0.02	**1**						
Review age	−0.00	0.02	0.02	0.01	0.01	−0.02	0.02	−0.01	0.00	0.00	−0.01	0.00	−0.00	**1**					
Average rating	0.00	0.00	0.00	0.02*	0.01	0.05***	0.57***	0.01	−0.02*	−0.03***	0.05***	−0.05***	0.01	0.03*	**1**				
Yelp tenure	0.15***	0.01	0.40***	0.24***	0.01	0.36***	−0.01	0.01	−0.01	0.00	0.01	−0.02*	−0.01	−0.01	−0.02	**1**			
Restaurant reputation	0.04***	0.07***	−0.01	0.00	0.10***	0.01	0.39***	0.01	−0.11***	−0.11***	0.19***	−0.19***	−0.01	0.01	0.22***	0.05***	**1**		
Restaurant popularity	−0.01	0.03**	−0.01	0.00	0.18***	0.00	0.11***	0.07***	−0.03**	−0.03***	0.11***	−0.06***	0.02*	0.02*	0.06***	0.04***	0.28***	**1**	
Restaurant age	−0.07***	0.04***	−0.02	−0.02	−0.01	−0.02*	−0.01	0.01	0.02*	−0.04***	−0.02	−0.00	0.00	0.03**	−0.02*	−0.03**	−0.04***	0.35***	**1**

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.
Note: Regarding the high correlations between some variables, we use variance inflation factor (VIF) to measure the severity of multicollinearity and find that the VIF values of all the variables are less than 5. Hence, the multicollinearity issue will not create a problem for our estimation results.

total number of words in the review, to determine the percentage of a review that falls into different categories. Here we mainly focus on affective processes (e.g., positive emotion, negative emotion, anger, anxiety), cognitive processes (e.g., certainty), and linguistic processes (e.g., word count). The total number of words in a review is measured as the word length of the review. Given that the ease of reading is important for review evaluation, we also calculate the readability of each review using the Gunning fog index. The word category "certainty" represents the key variable of interest. The certainty category includes 83 associated words, such as absolute, certain, clearly, commit, completely, confidence, fact, must, definitely, totally, and every. Therefore, certainty is measured as the percentage of the number of certainty-related words divided by the total number of words in a review. In addition, we also calculate positivity, negativity, anger, and anxiety using the number of words related to positive emotions, negative emotions, anger, or anxiety divided by the total number of words. In terms of associated words in these categories, please refer to Appendix C.

5.3. Variables and measurement

Dependent Variable. Below each review, Yelp.com presents the question "Was this review…?" and offers the options of "useful," "funny," and "cool." In this study, we focus only on the "useful" option. A review that has received at least one useful vote displays its number of useful votes next to the "useful" icon. Thus, review usefulness is measured as the number of useful votes; a high value of usefulness indicates a useful review. Review usefulness is our dependent variable of interest.

Independent Variables. We regard review certainty, reviewer expertise, reviewer popularity, restaurant niche width, and their interactions as predictors of review usefulness. The certainty is measured as the percentage of the number of certainty-related words divided by the total number of words in a review with LIWC as explained in the "Data Preparation" section. Table 2 lists the measures of the other three variables.

Control Variables. The control variables are the other characteristics of review, reviewer, and restaurant. For review characteristics,[4] we control for readability [22], review length, review rating and squared terms of rating [42], anger, anxiety [70], and review age [54]. To accurately control for the emotional valence of textual reviews, we also control for the percentage of the positive and negative emotional words in a review calculated by the LIWC. For reviewer characteristics, we control for status, time spent on Yelp, and average rating [22]. Finally, for restaurant characteristics, we control for the price range of a restaurant and the age of a restaurant at the time of the data collection. Given that the restaurants opening date was not available to us, we use the date of the first review of a restaurant as a proxy for the opening date of the restaurant to calculate restaurant age. In addition, we also control for the total number of reviews a restaurant has received (i.e., popularity of the restaurant). And we use the average star rating of a restaurant as a proxy for restaurant reputation, assuming that a high rating indicates a good restaurant [44]. We include this variable in both the logit model and the NB model as a control. Tables 3, 4, and 5 present the measures,

[4] In terms of including view count to control review visibility, we asked Yelp about the view count data but unfortunately did not get any more information about this (the response from Yelp can be seen from the email screenshot in Appendix D). We thus incorporate this point as a limitation of the current study and call for future research on this issue.

descriptive statistics, and correlation matrix of all variables, respectively.[5,6]

6. Estimation results

6.1. Model specification

When modeling count data—i.e., the number of useful votes of a review—we consider two issues: first, whether or not a useful vote is given at all, and second, how many useful votes are made on reviews with at least one useful vote. We propose the use of ZINB model for estimation primarily because it is appropriate to model the over-dispersed count data with excess zeros [15]. Our data not only demonstrate overdispersion with the variance of count of "useful" votes larger than the mean (as depicted in Table 4, variance (usefulness) = 2.69, mean (usefulness) = 0.71), but also contain excess zeros with a large percentage of reviews (63.22%) with no useful votes. Using the ZINB Poisson model, we can test two-stage models in which the logit and the standard NB models are estimated jointly; the logit model estimates the probability of a review receiving zero useful votes and the NB model predicts the conditional number of useful votes. Extant studies have mainly used the percentage-based approach to predict review usefulness, leaving out reviews without votes. We can then empirically investigate and understand why different reviews receive zero or various usefulness votes.

$$Logit\left(Y_{i,j,k}{}^{*}\right) = \alpha_0 + \alpha_1 Rest_j + \alpha_2 Reviewer_k + \alpha_3 \mathrm{Rating}_{\mathrm{i,j,k}} + \alpha_4 \mathrm{Rating}^2_{\mathrm{i,j,k}} + \alpha_5 Timespan + \varepsilon'_{i,j,k} \quad (1)$$

The logit model that determines whether a review receives a useful vote is specified in Eq. (1), which includes restaurant features (i.e., restaurant niche width, price, reputation, popularity, and restaurant age), reviewer characteristics (i.e., reviewer Yelp tenure, expertise, popularity, and status), review valence (i.e., rating and its squared terms), and age of the review. In line with existing empirical studies, customers' perceptions of online reviews (e.g., helpful or not) are largely determined by review ratings (e.g., rating valence and extremity; [42]), reviewer traits (e.g., number of past reviews written) [22], whether reviewer is deemed "elite" or not, number of friends [54], Yelp tenure of reviewer [68], organizational features (i.e., store reputation and popularity; [70]), restaurant price, and niche width [35]. Interaction terms are excluded from the logit model because we believe that the interactions among review, reviewer, and contextual features are more relevant to the number of useful votes given than they are to the probability of not receiving any useful votes.

On the other hand, the NB model presents the number of usefulness votes as specified in Eq. (2). The model estimates the effects of review certainty, reviewer expertise, reviewer popularity, restaurant niche width, and interactions among review certainty, reviewer expertise, reviewer popularity, restaurant niche width, as well as the control variables, in line with the existing literature. The ZINB model allows for the existence of different sets of predictors in the logit and the standard NB models [15].

$$Log\left(Y_{i,j,k}\right) = \beta_0 + \beta_1 Cer_{i,j,k} + \beta_2 Rev_k + \beta_3 Fans_k + \beta_4 Nichew_j + \beta_5 TwoInter_{i,j,k} + \beta_6 ThreeInter_{i,j,k} + \beta_7 Contr_{i,j,k} + \varepsilon_{i,j,k} \quad (2)$$

where

$Y_{i,j,k}{}^{*}$ is the probability of zero usefulness votes on review i of business j by reviewer k;

$Y_{i,j,k}$ is the expected number of usefulness votes on review i of business j by reviewer k;

$Rest_j$ is a matrix of variables about restaurant j, including $\mathrm{restaurant\_reputaion}_j$, $\mathrm{restaurantage}_j$, $\mathrm{restaurant\_popularity}_j$, *and* price_j;

$Reviewer_k$ is a matrix of variables about reviewer k, including status_k, $\mathrm{Yelp\_tenure}_k$;

$\mathrm{Cer}_{i,j,k}$ is the certainty of review i of business j by reviewer k;

Rev_k is the number of reviews written by reviewer k;

$Fans_k$ is the number of fans of reviewer k;

$NicheW_j$ is the niche width of restaurant j;

$\mathrm{TwoInter}_{i,j,k}$ is a matrix of two-way interaction terms, including $\mathrm{Cer}_{i,j,k}*\mathrm{Fans}_k$, $\mathrm{Cer}_{i,j,k}*\mathrm{Rev}_k$, $\mathrm{Fans}_k*\mathrm{Rev}_k$, $\mathrm{Fans}_k*\mathrm{NicheW}_j$, $\mathrm{Rev}_k*\mathrm{NicheW}_j$, $\mathrm{Cer}_{i,j,k}*\mathrm{NicheW}_j$;

$\mathrm{ThreeInter}_{i,j,k}$ represents a matrix of three-way interaction terms, including $\mathrm{Cer}_{i,j,k}*\mathrm{Fans}_k*\mathrm{NicheW}_j$, $\mathrm{Cer}_{i,j,k}*\mathrm{Rev}_k*\mathrm{NicheW}_j$;

$\mathrm{Controls}_{i,j,k}$ represents a matrix of control variables for review i of business j by reviewer k, including $\mathrm{rating}_{i,j,k}$, squared term of $\mathrm{rating}_{i,j,k}$, $\mathrm{length}_{i,j,k}$, $\mathrm{readability}_{i,j,k}$, $\mathrm{anger}_{i,j,k}$, $\mathrm{anxiety}_{i,j,k}$, $\mathrm{positivity}_{i,j,k}$, $\mathrm{negativity}_{i,j,k}$, $\mathrm{Yelp\_tenure}_k$, status_k, $\mathrm{Avguser\_rating}_k$, $\mathrm{restaurant\_reputaion}_j$,

Table 6
ZINB Estimation Results.

Variables	Logit model estimating zero useful votes			
	Model 1	Model 2	Model 3	Model 4
Rating	2.4248	0.8791	0.7800	0.7163
Squared rating	–0.2578	–0.0549	–0.0418	–0.0417
Reviewer status	–1.8172***	–2.6584*	–2.5202**	–2.5048***
Reviewer Yelp tenure	–0.0025**	–0.0025**	–0.0025**	–0.0023**
Restaurant popularity	0.0001	–0.0001	–0.0001	0.0002
Restaurant reputation	–0.8352**	–0.9015***	–0.8835***	–0.8955***
Restaurant age	0.0022*	0.0024**	0.0024**	0.0021**
Price: $	–1.4016*	–0.2817	–0.3406	–0.5226
Price: $$	–1.1451	–0.2337	–0.3114	–0.5136
Price: $$$	–1.8416*	–1.1719	–1.1569	–1.3298
Price: $$$$	0.0000	0.0000	0.0000	0.0000
Review age	0.2642***	0.2790***	0.2756***	0.2616***

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

[5] We further postulate that writing an online review is a learning process that meets the saying "practice makes perfect." In other words, the more reviews a reviewer has written, the more experiences he/she accumulates, and finally the more likely he/she possesses expertise on Yelp.com [2]. Thus, our conceptualization of expertise highlights the experience in review writing and the accumulated knowledge in specific areas, which are supposed to affect the quality of the reviews as perceived by consumers. Thus, based on this conceptualization of reviewer expertise, we believe that our measure of expertise can support the related conclusions.

[6] We have conducted estimations using elite's tenure, status and review rating as the measure of reviewer expertise and tested our hypotheses. The estimation results are in Appendices E1, E2, and E3. However, these results failed to provide significant evidence for the two hypotheses associated with expertise (i.e., H1 and H3). One possible reason for this is that reviewers with long tenure, or reviewers as elites, or reviewers with high ratings do not necessarily write many reviews and may thus not accumulate the necessary amount of knowledge to be considered an expert [2]. Hence, we believe that the number of reviews previously written may be the appropriate measure of reviewer expertise in the current Yelp context.

Table 7
ZINB Estimation Results.

Variables	NB model estimating no. of useful votes Model 1	Model 2	Model 3	Model 4
Model 1: Control effects				
Rating	–0.2871**	–0.4970***	–0.5086***	–0.5416***
Squared rating	0.0321*	0.0614***	0.0633***	0.0692***
Length	0.0001	0.0002	0.0002	0.0002
Anger	–0.0003	0.0231	0.0248	0.0248
Anxiety	–0.0068	0.0047	0.0035	–0.0033
Positivity	–0.0021	–0.0026	–0.0027	–0.0033
Negativity	0.0211	0.0090	0.0099	0.0063
Readability	0.0015	0.0027	0.0026	0.0027
Log (review age)#	1	1	1	1
Reviewer status	1.3298***	0.8841***	0.8832***	0.4584***
Reviewer Yelp tenure	0.0001	0.0000	–0.0000	–0.0001
Reviewer average rating	0.0302	0.0580	0.0601*	0.0606*
Restaurant reputation	0.1802***	0.1937***	0.1893***	0.1578**
Restaurant popularity	0.0000	0.0000	0.0000	0.0001
Restaurant age	–0.0010***	–0.0009***	–0.0009***	–0.0010***
Price: $	–0.4646*	–0.0062	–0.0378	–0.1592
Price: $$	–0.2374	0.1921	0.1549	0.0290
Price: $$$	–0.2546	0.1208	0.0878	–0.0145
Price: $$$$	0.0000	0.0000	0.0000	0.0000
Model 2: Linear effects				
Review certainty		0.0083	0.0123	0.0149
Reviewer expertise		0.0005**	0.0005**	0.0011***
Reviewer popularity		0.0152***	0.0145***	0.0430***
Restaurant niche width		–0.0664**	–0.0654**	–0.0679**
Model 3: Two-way interaction effects				
Certainty*expertise (**H1**)			0.0001	–0.0001
Certainty*popularity (**H2**)			–0.0041**	0.0016
Certainty*niche width				0.0184
Expertise*popularity				–0.0000***
Expertise* niche width				–0.0000
Popularity* niche width				0.0011
Model 4: Three-way interaction effects				
Certainty*expertise*niche width (**H3**)				–0.0003**
Certainty*popularity*niche width (**H4**)				0.0058***

***$p < 0.001$; **$p < 0.01$;*$p < 0.05$.
#As suggested by Allison (1999), we included the natural log of the review age as a predictor with a regression coefficient equal to 1 with the purpose of incorporating variable observation periods while maintaining the Poisson error structure of the data.

restaurantage_j, $\text{restaurant\_popularity}_j$, price_j;

$\varepsilon_{i,j,k}{}^{/\text{prime}}$is the residual error term of Eq. (1) and $\varepsilon_{i,j,k}$ is the residual error term of Eq. (2);

Note that Rev_k and Fans_k are treated as static variables—i.e., we assume no significant changes in these reviewer characteristics during our short three-month observational time window.

6.2. Estimation results

We estimate our ZINB model is estimated in SAS using Proc Genmod, and control for the variable length of the observational periods of the reviews by including the natural log of review age using the offset option—according to which its regression coefficient is equal to 1 [3]. We conducted the Vuong test to compare the ZINB model with the standard NB model, and obtained results for the Schwarz adjusted statistic ($z = 8.2199$, $p < 0.001$). The findings suggest that the ZINB model is a significant improvement over the standard NB model. The scaled Pearson chi-square statistic is significantly different from 1 (scaled Pearson X2 = 10,658.0673, $p < 0.001$), thereby providing evidence for overdispersion.

To clarify our hypothesized effects, we use stepwise regression with four blocks of variables: controls (Model 1), linear effects (Model 2), two-way interaction effects (Model 3), and three-way interaction effects (Model 4), each of which estimates the logit and NB models jointly. Tables 6 and 7 demonstrate the estimation results.[7] The same set of variables is used for logit regression across all four models. As shown in Table 6, regardless of the models used, the logit results show that restaurant reputation consistently reduces the probability of a review obtaining zero useful votes. In other words, reviews about restaurants with high star ratings tend to receive useful votes. Since customers perceive a restaurant with a high rating (e.g., five stars) as high quality, it easily attracts considerable attention and its reviews tend to be read and evaluated. In addition, the results of the logit model show that the reviewer's time spent on Yelp also decreases the probability of a review obtaining zero useful votes. In other words, the probability of a review receiving zero useful votes is low for reviewers that have been writing reviews at Yelp.com for a long time. This result is attributed to the logic that the longer reviewers stay on a website, the more familiar they become with the environment and the regulations of the website. Such familiarity may help reviewers more easily capture customer preferences, enabling them to write useful reviews.

For NB regression, as shown in Table 7, we first estimate Model 1. The control effects are partially consistent with the prior literature. First, the negative reviews ($\beta = -0.2871$, $p < 0.001$), especially those with extreme ratings ($\beta = 0.0321$, $p < 0.001$), are rated more useful than positive reviews. This result is consistent with the findings obtained by Mudambi & Schuff [42]. Second, reviews about new ($\beta = -0.0010$, $p < 0.001$) restaurants with good reputations ($\beta = 0.1802$, $p < 0.001$) are considered more useful than reviews about restaurants with bad reputations that have been in business for a long time. Third, the coefficient of reviewer status ($\beta = 1.3298$, $p < 0.001$) is significant and positive, thereby suggesting that reviews posted by "elite" reviewers can be predicted to be useful; such a finding is in line with the observations of

[7] We got our estimation results with standardized variables.

Table 8
Estimation results when including other two-way interactions.

Variables	Model 1	Model 2	Model 3
Model 1: Test other four two-way interactions			
Rating	–0.4876***	–0.4986***	–0.5427***
Squared rating	0.0601***	0.0618***	0.0696***
Length	0.0002	0.0002	0.0002
Anger	0.0157	0.0152	0.0238
Anxiety	–0.0059	–0.0029	–0.0119
Positivity	–0.0054	–0.0064	–0.0055
Negativity	0.0028	0.0021	0.0051
Readability	0.0029	0.0028	0.0030
Log (review age)[#]	1	1	1
Reviewer status	0.8810***	0.8823***	0.4575***
Reviewer Yelp tenure	0.0000	–0.0000	–0.0001
Reviewer average rating	0.0556	0.0583	0.0592
Restaurant reputation	0.1941***	0.1928***	0.1564*
Restaurant popularity	0.0000	0.0000	0.0001
Restaurant age	–0.0010***	–0.0009***	–0.0010
Price: $	0.0050	–0.0319	–0.1795***
Price: $$	0.2004	0.1576	0.0042
Price: $$$	0.1309	0.0936	–0.0418
Price: $$$$	0.0000	0.0000	0.0000
Review certainty	0.0082	0.0146	0.0169
Reviewer expertise	0.0005**	0.0005**	0.0011***
Reviewer popularity	0.0151***	0.0136***	0.0430***
Restaurant niche width	–0.0640**	–0.0622**	–0.0674**
*Popularity *positivity*	0.0006	0.0009	0.0013*
*Popularity *negativity*	–0.0017	–0.0003	–0.0026*
*Expertise *positivity*	0.0000	0.0000	–0.0000
*Expertise*negativity*	0.0004*	0.0003	0.0002
Model 2: Test H1&H2			
Certainty*expertise (**H1**)		0.0001	–0.0001
Certainty*popularity (**H2**)		–0.0040**	0.0003
Model 3: Test H3&H4			
Certainty*niche width			0.0196
Popularity* niche width			0.0021
Expertise*popularity			–0.0001
Expertise* niche width			–0.0000***
Certainty*expertise*niche width (**H3**)			–0.0003**
Certainty*popularity*niche width (**H4**)			0.0062***

Ghose & Ipeirotis [22].

Model 2 validates the linear effects of review and reviewer characteristics on review usefulness. The coefficients of reviewer popularity ($\beta = 0.0152, p < 0.001$) and expertise ($\beta = 0.0005, p < 0.01$) are significant and positive, thereby suggesting that reviews posted by well-known reviewers or by those with a lot of posting experience can be predicted to be useful. Furthermore, the coefficient of restaurant niche width ($\beta = -0.0664$, $p < 0.01$) is significant and negative, thereby indicating that the reviews of narrowly positioned restaurants are more useful than those of broadly positioned restaurants.

Model 3 tests our hypotheses H1 and H2. The coefficient of the two-way interaction between review certainty and reviewer popularity ($\beta = -0.0040, p < 0.01$) is significant and negative, which suggests that H2 is supported. However, we failed to secure significant evidence for H1, which postulates the interaction between review certainty and reviewer expertise ($\beta = 0.0001$, $p = 0.1940$).

Model 4 tests our hypotheses H3 and H4. The coefficient of the three-way interaction among review certainty, reviewer expertise, and restaurant niche width ($\beta = -0.0003$, $p < 0.01$) is significant and negative, whereas the coefficient of the three-way interaction among review certainty, reviewer popularity, and restaurant niche width ($\beta = 0.0058$, $p < 0.001$) is significant and positive, which thereby supports both hypotheses. Besides, we have also plotted the interaction effects for all the four hypotheses in Appendix F: Panels A–D.[8]

6.3. Robustness checks

Including other two-way interactions. In our main model estimation, we do not include the interactions between popularity and positivity, popularity and negativity, experts and positivity, and popularity and negativity. Here we include these two-way interactions (italicized) to see if the result remains the same. As shown in Table 8, with the inclusion of these interactions, the results are robust.

Follow-up estimation. Given that reviewer characteristics may change over time, we test the robustness of our findings using a follow-up estimation. Here we focus on reviews in the next month after our main data collection. In this follow-up dataset, there are 3723 reviews written by 2689 reviewers of 1565 restaurants in the state of Arizona, U.S.A. on January 2014. As shown in Table 9, the results are robust and are consistent with our main estimation.

Controlling for the number of friends. In our main model estimation, we do not control for the number of the reviewer's friends. Since the number of friends may be observed by the review recipients and might play a role in influencing their judgment on review usefulness, here we include Friend_no (italicized) as a control variable to check if our result remains the same. As shown in Table 10, after controlling for the number of friends, the results are consistent.

7. Discussion

7.1. Summary of results

We examine the joint effects of review, reviewer, and organization characteristics on review usefulness by building on dual-process theory. By applying the paradigm of expert and popularity endorsements [6] explained by social influence theory, we offer a conceptualization of what constitutes a useful review. Our empirical results—obtained by utilizing restaurant reviews from Yelp.com with ZINB regression—provide support for our model and for most of our hypotheses. High certainty reviews receive fewer usefulness votes when written by popular reviewers followed by many fans than when written by less popular reviewers. We presume that this condition is attributable to the fact that the signal of popularity (number of fans) tends to inspire mindless heuristic processing among review recipients, thereby mitigating the cognitive efforts they devote to understanding the content of such reviews.

For the moderating effect of expertise (number of reviews written),

[8] We acknowledge that some of the key coefficients are relatively small by magnitude. For example, we have –0.0003 of the three-way interaction of certainty, expertise, and niche width. Because we are running Poisson regression with a three-way interaction, the interpretation of the magnitude following the logic of H3 shall be for each additional cuisine category of a restaurant, the expected moderating effect of expertise on the impact of certainty on usefulness votes is reduced by about 1 [i.e., exp (0.0003)]. The practical significance of the coefficient depends on the persuasion power of the marginal effects of this one-vote change. Because our research focuses on the statistical significance associated with the test of whether the coefficient is different from 0, rather than the numerical value, we acknowledge the limitation of our research and call for future research on the above issue.

Table 9
Estimation results in the next month after data collection.

Variables	NB model estimating no. of useful votes Model 1	Model 2	Model 3	Model 4
Model 1: Control effects				
Rating	–0.2108	–0.4548**	–0.4680**	–0.4973***
Squared rating	0.0198	0.0602*	0.0622**	0.0648**
Length	–0.0001	0.0001	0.0001	0.0001
Anger	–0.0257	–0.0332	–0.0379	–0.0470
Anxiety	0.0567	0.1214	0.1250	0.1184
Positivity	0.0124	0.0154	0.0166	0.0162
Negativity	–0.0073	–0.0135	–0.0110	–0.0057
Readability	–0.0025	0.0005	0.0005	0.0027
Log (review age)[#]	1	1	1	1
Reviewer status	1.2724***	0.6854***	0.6819***	0.4645***
Reviewer Yelp tenure	0.0005	0.0000	0.0000	0.0000
Reviewer average rating	–0.0038	0.0356	0.0380	0.0511
Restaurant reputation	0.1848	0.1108	0.1064	0.1331
Restaurant popularity	–0.0001	–0.0002	–0.0002	–0.0002
Restaurant age	–0.0008**	–0.0007*	–0.0008**	–0.0007**
Price: $	0.6637	0.2859	0.2514	0.2859
Price: $$	0.8353	0.5880	0.5766	0.5810
Price: $$$	0.4120	0.2657	0.2580	0.2830
Price: $$$$	0.0000	0.0000	0.0000	0.0000
Model 2: Linear effects				
Review certainty		0.0139	0.0098	0.0073
Reviewer expertise		0.0012***	0.0009**	0.0004
Reviewer popularity		0.0107***	0.0162***	0.0562***
Restaurant niche width		0.0429	0.0377	0.0118
Model 3: Two-way interaction effects				
Certainty*expertise (**H1**)			–0.0003	–0.0001
Certainty*popularity (**H2**)			0.0084***	0.0011
Certainty*niche width				0.0338
Popularity* niche width				0.0075**
Expertise* niche width				–0.0002
Expertise*popularity				–0.0000***
Model 4: Three-way interaction effects				
Certainty*expertise*niche width (**H3**)				–0.0007**
Certainty*popularity*niche width (**H4**)				0.0103***

we argue that reviewer expertise should increase the extent to which recipients believe that the reviewer devoted significant cognitive effort to writing the review; we postulated that such an increase would foster the recipients' increased engagement with the review, thereby improving the perception of usefulness related to the high certainty review. However, we failed to obtain the empirical evidence necessary to support our hypothesis (H1) concerning this issue. One of the reasons might be that the "number of reviews written" is a better measure of "experience" than of "expertise." For example, reviewers may have visited many restaurants (i.e., experienced reviewers) but still do not possess a superior knowledge repository and structure for evaluating restaurants (i.e., expert reviewers). Given the limited validation of the effect of reviewer expertise, future measurements of expertise should be refined (e.g., the number of useful votes a reviewer has received before writing the focal review, past restaurant reviews and familiarity with similar restaurants, and reviewer reputation). Given access to appropriate data, we hope to deploy such measures in the future.

In addition, we found that a wide niche (i.e., broadly positioned restaurants) magnifies the usefulness of high certainty reviews by popular reviewers while mitigating the usefulness of high certainty reviews by expert reviewers, thereby supporting our hypotheses. We postulate that this circumstance can be attributed to the fact that the signal of wide niche (e.g., a restaurant offering multiple cuisines) increases evaluation difficulties; therefore, this difficulty readily activates customers' systematic processing. By contrast, a narrow niche (e.g., a restaurant that offers only one type of food) improves ease of understanding and tends to strengthen systematic processing, causing review recipients to absorb knowledge and internalize the information shared by expert reviewers.

We also show that our model offers a better prediction of review usefulness. We performed additional analysis (Appendix G) comparing our empirical results across ZINB, standard Poisson, NB, and zero-inflated Poisson. We found that the goodness-of-fit index AIC and BIC of ZINB suggest the best model fit. Therefore, we chose the ZINB model to provide better prediction of review usefulness.

7.2. Theoretical implications

Drawing on dual-process theory and social influence theory, we provide a theoretical model that articulates the interactions among review certainty, reviewer expertise, reviewer popularity, and organization niche width on review usefulness. We grounded the real-world count of usefulness votes in theory by linking it to the concept of elaboration likelihood. Our findings help extend the literature on online customer reviews along multiple lines.

First, the majority of the prior research on review usefulness/helpfulness has focused on the easily observable determinants, such as numeric ratings, review length, and reviewer reputation. Our research adds to the merging body of the text mining literature (see, e.g., [27, 35]) by emphasizing the effects of certainty embedded in review content on review usefulness. We document evidence on the adaptive nature of review certainty in review usefulness and report robust evidence on the important role of reviewer characteristics—e.g., popularity, regarding the usefulness of high certainty reviews—thus clarifying some of the mixed evidence presented in the certainty literature. As we mentioned at the beginning of this paper, Sniezek & Van Swol [63] empirically demonstrate the positive effect of certainty on information trustworthiness and acceptance, whereas Yin et al. [70] indirectly present the negative effect of certainty embedded in emotions as one dimension of cognitive appraisal on the elaboration likelihood. Our findings empirically confirm a contingent model showing that, depending on reviewer popularity, the certainty embedded in reviews either strengthen (e.g., concerning a reviewer with a few fans) or weaken (e.g., concerning a

Table 10
Estimation results after controlling for the number of friends.

Variables	NB Model estimating no. of useful votes			
	Model 1	Model 2	Model 3	Model 4
Model 1: Control effects				
Rating	–0.2906**	–0.4947***	–0.5062***	–0.5403***
Squared rating	0.0325*	0.0610***	0.0629***	0.0690***
Length	0.0001	0.0002	0.0002	0.0002
Anger	0.0011	0.0233	0.0251	0.0249
Anxiety	–0.0067	0.0046	0.0037	–0.0034
Positivity	–0.0021	–0.0026	–0.0027	–0.0033
Negativity	0.0201	0.0089	0.0097	0.0065
Readability	0.0017	0.0027	0.0026	0.0027
Log (review age)[#]	1	1	1	1
Reviewer status	1.3156***	0.8847***	0.8834***	0.4591***
Reviewer Yelp tenure	0.0001	0.0000	–0.0000	–0.0001
Reviewer average rating	0.0352	0.0592*	0.0614*	0.0606*
Restaurant reputation	0.1749**	0.1935***	0.1891***	0.1578**
Restaurant popularity	0.0000	0.0000	0.0000	0.0001
Restaurant age	–0.0010***	–0.0010***	–0.0009***	–0.0010***
Price: $	–0.4706*	–0.0141	–0.0457	–0.1614
Price: $$	–0.2463	0.1854	0.1484	0.0279
Price: $$$	–0.2644	0.1157	0.0828	–0.0152
Price: $$$$	0.0000	0.0000	0.0000	0.0000
Friend_no	–0.0126**	–0.0044	–0.0044	–0.0006
Model 2: Linear effects				
Review certainty		0.0082	0.0123	0.0149
Reviewer expertise		0.0005**	0.0005**	0.0011***
Reviewer popularity		0.0148***	0.0141***	0.0429***
Restaurant niche width		–0.0659**	–0.0649**	–0.0678**
Model 3: Two-way interaction effects				
Certainty*expertise (**H1**)			0.0001	–0.0001
Certainty*popularity (**H2**)			–0.0039**	0.0016
Certainty*niche width				0.0185
Expertise*popularity				–0.0000***
Expertise* niche width				–0.0000
Popularity* niche width				0.0011
Model 4: three-way interaction effects				
Certainty*expertise*niche width (**H3**)				–0.0003**
Certainty*popularity*niche width (**H4**)				0.0058***

reviewer with many fans) the usefulness of reviews. By doing so, we generate insights about the certainty effect, demonstrate that it varies according to reviewer popularity.

Second, our findings supplement the review usefulness/helpfulness literature (see, e.g., [19, 42, 70]) by identifying two reviewer characteristics—expertise and popularity and their interactions with review certainty. We find that a reviewer followed by many fans signals low usefulness of the certainty-embedded review. These findings imply the importance of match between review and reviewer in producing a useful review. Besides, our findings also extend dual-process theory by examining reviewer popularity, an additional peripheral cue that has received less attention in dual-process research but is commonly found in the context of social media.

Third, this study provides new insights into the role of context in influencing research findings [24]. We identified a context-specific factor—organization niche width—to formulate context-sensitive predictors of the persuasion of online customer reviews. Considering that social communications occur in different contexts, such as hotel, restaurant, groceries, etc., e-WOM has different implications for processing messages in different contexts. In our study, we focus on the restaurant context. In light of the specific restaurant contextual feature—i.e., niche width, we find that restaurant niche width magnifies the usefulness of the certainty-embedded review by a popular reviewer while lowers the usefulness of the certainty-embedded review by an expert reviewer. Our findings address the importance of incorporating contextual factors into theory development and empirical studies.

7.3. Practical implications

In the context of product quality uncertainty, consumers have to balance their own knowledge with inferences drawn from the opinions of those who have already sampled the products. As such, research has shown that online customer reviews, especially useful reviews [11], can serve as important references in decision-making [40, 61]. Our study offers some actionable implications for managers as well as retailers in the prediction and utilization of useful reviews.

First, our findings regarding the determinants of review usefulness offer prominent benefits for online third-party review websites in the screening and selection of useful information. Currently, the review voting system is post hoc—i.e., reviews can only be judged as useful after accumulating useful votes. However, our findings can enhance ante hoc mechanisms concerning review recommendations. For example, rather than relying on fixed features (e.g., date and rating), Yelp.com could consider the certainty factor in updating its default sorting mechanism ("Yelp Sort") by moving high certainty reviews to the top of a list of ratings, thus simplifying users' access to valuable reviews.

Second, our findings with respect to the moderating effects of organizational niche width imply that restaurant managers should view online customer reviews as a double-edged sword and adopt differentiated strategies when attempting to increase review efficacy for restaurants with different niche widths. For example, concerning a restaurant offering multiple cuisines (e.g., one tagged with "Mediterranean," "Greek," and "Middle Eastern"), the potential large variance of opinions embedded in reviews from different reviewers with various preferences can amplify the difficulty that potential customers encounter in attempting to fully understand the restaurant. Taking this circumstance into account, managers might encourage popular customers with many fans to write reviews for the restaurant, thus taking advantage of the identification impacts associated with popular reviewers. By contrast, for a restaurant that only offers one type of food, managers should seek to strengthen customers' understanding of the restaurant by soliciting reviews written by expert reviewers who have professional knowledge and rich experience about the specific cuisine.

Finally, at a broad level, our findings also offer some managerial implications for social media platforms (e.g., Facebook and Twitter), in general. With the emergence of social buttons in social media (e.g., "like," "share," and "comment" icons accompanying posts), users can interact with other people by clicking corresponding social buttons. Consequently, this activity can then turn into numbers on the associated button counter to signal the attractiveness of a post [28]. Given the critical importance of customer engagement or interactivity in e-commerce, a frequently discussed question for managers when implementing social media marketing is how to reinforce social interactivity. Our findings that predict the factors that will cause a review to be voted "useful" can also offer insights into what topics or posts might attract a higher level of interaction in terms of social button activity.

7.4. Limitations and future research

Our study has a few limitations. First, we examined restaurant reviews only; hence, the generalizability of our findings to other business categories (e.g., hotel, beauty) or contexts is unclear and should be subjected to further empirical inquiry. We chose Arizona as the focal location simply because the Yelp Academic dataset was limited to businesses in Arizona. Future research should test the generalizability of our model using data from other geographical locations/cultures—e.g., a comparison between Canadians and Americans. Second, Yelp's sorting approach and the position of the reviews may also play a key role in the influence on review usefulness. While we have controlled some variables that may influencing the position and thus the visibility of the reviews—e.g., the recency variable. Our dataset does not contain any fields directly related to the sorting mechanism. We thus acknowledge this limitation and call for future research in this direction. Third, our conceptualization and the associated operationalization of reviewer expertise may lead to the two issues—i.e., 1) a reviewer can be classified as an expert by writing many (ungrounded) negative reviews/complaints and 2) a person who processes the expertise of food may not have time to write many reviews. Unfortunately, with the field data we have, we cannot directly access the significance of these issues. We thus acknowledge them as the limitations of our study and call for future research on the issues. Finally, we measure reviewer expertise as the number of previous reviews written. Other features such as "Review of the day" or "check-in" may also describe the level of reviewer expertise. Unfortunately, with the Yelp Academic dataset we cannot directly access these data. We thus acknowledge this limitation and call for future research to improve the expertise measurement and incorporate more features.

Our study also offers a number of interesting avenues for future research. First, since using the Yelp.com data has the advantage of being an objective approach compared with other methods that capture subjective perceptions, and given that the controlled experimental method has the advantage of increasing internal validity, future experimental studies could provide converging evidence for our model. Second, text-mining techniques enable interesting areas for future research. Content analysis can be used to obtain additional information from review content to further explain what constitutes a useful review. Future research could examine other textual features of reviews, such as the associative words to certainty (e.g., absolutely not, without certainty), information richness and possible interaction effects. Third, our research is essentially a cross-sectional study without considering the change of review/reviewer characteristics over time and their dynamic impacts. Future research may conduct longitudinal investigation in this direction. Finally, our predictive model could also be extended to include visual determinants of review usefulness, including the number of pictures posted by reviewers, and the visual quality of pictures embedded in a review. Currently, online customer reviews include not only textual content and numeric ratings, but also pictures. Future studies could extend the current predictive model to examine how the number and quality of pictures influence review usefulness.

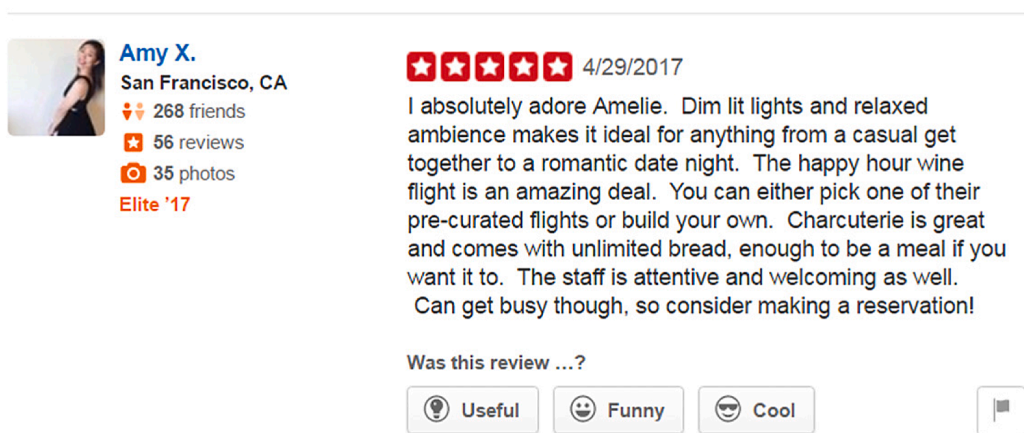
8. Conclusion

In conclusion, our research is a further step toward conceptualizing a framework for review usefulness and testing the joint effects of review certainty, reviewer characteristics, and organizational niche width. This is anticipated to stimulate further scholarly work in the pivotal field of social media analytics.

CRediT authorship contribution statement

Jing Li: Data curation, Writing – original draft, Writing – review & editing, Methodology. **Xin Xu:** Conceptualization, Validation, Writing – review & editing. **Eric W.T. Ngai:** Conceptualization, Validation.

Appendix A: Sceeenshots of high certainty reviews on yelp.com



Appendix B: Test hypotheses using the dataset 6 months before data collection

Variables	NB Model estimating no. of useful votes			
	Model 1	Model 2	Model 3	Model 4
Model 1: Control effects				
Rating	−0.4620***	−0.6246***	−0.6272***	−0.6400***
Squared rating	0.0511***	0.0756***	0.0761***	0.0793***
Length	0.0003*	0.0004**	0.0004**	0.0004***
Anger	−0.0015	0.0003	0.0014	0.0030
Anxiety	−0.0208	−0.0140	−0.0164	−0.0178
Positivity	0.0011	0.0031	0.0029	0.0021
Negativity	0.0111	0.0087	0.0087	0.0085
Readability	0.0079**	0.0060*	0.0060*	0.0052
Log (review age)#	1	1	1	1
Reviewer status	1.4382***	1.0099***	1.0116***	0.6605***
Reviewer Yelp tenure	0.0003*	0.0002	0.0002	0.0001
Reviewer average rating	0.364	0.0576**	0.0585**	0.0613**
Restaurant reputation	0.2711***	0.3038***	0.3012***	0.2852***
Restaurant popularity	0.0001	0.0002	0.0002	0.0002
Restaurant age	−0.0014***	−0.0013***	−0.0013***	−0.0013***
Price: $	−0.2124	−0.0609	−0.0785	−0.0613
Price: $$	−0.0682	0.0884	0.0675	0.0879

(continued on next page)

(*continued*)

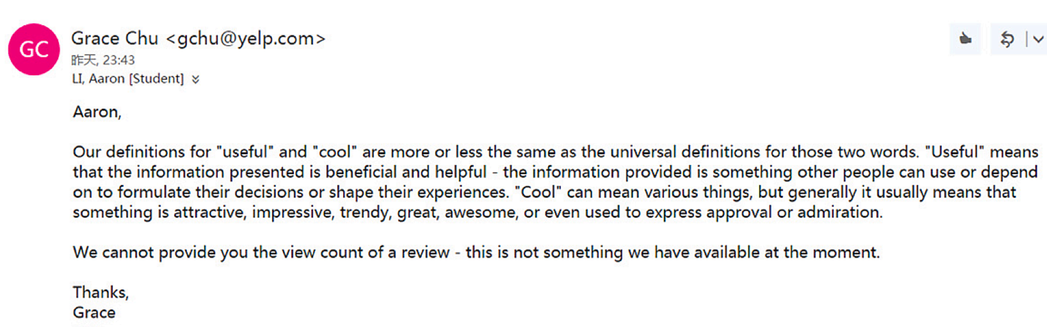
Variables	NB Model estimating no. of useful votes			
	Model 1	Model 2	Model 3	Model 4
Price: $$$	–0.0461	0.0606	0.0397	0.0780
Price: $$$$	0.0000	0.0000	0.0000	0.0000
Model 2: Linear effects				
Review certainty		0.0109	0.0118	0.0126
Reviewer expertise		0.0002*	0.0002	0.0007***
Reviewer popularity		0.0183***	0.0179***	0.0416***
Restaurant niche width		–0.0416**	–0.0413**	–0.0380*
Model 3: Two-way interaction effects				
Certainty*expertise (**H1**)			0.0001	0.0001
Certainty*popularity (**H2**)			–0.0027	–0.0014
Certainty*niche width				0.0178
Expertise*popularity				–0.0000***
Expertise* niche width				–0.0000
Popularity* niche width				–0.0012
Model 4: three-way interaction effects				
Certainty*expertise*niche width (**H3**)				–0.0002*
Certainty*popularity*niche width (**H4**)				0.0050***

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.
#As suggested by Allison (1999), we included the natural log of the review age as a predictor with a regression coefficient equal to 1 with the purpose of incorporating variable observation periods while maintaining the Poisson error structure of the data.

AppendiX C: Liwc dictionary sample for our key variables

Category	Associated Words
Certainty	Absolute, always, never, absolutely, all, altogether, apparent, certain, clear, commit, completely, confidently, correct, defined, definite, definitely, directly, distinct, entire, essential, every, evident, extremely, fact, frankly, fundamental, fundamentally, indeed, must, obvious, perfect, proof, prove, pure, sure, total, totally, true, truly, truth, unambiguous, undeniably, undoubtedly, unquestionably, wholly, etc.
Positive Emotion	Accept, party, accepted, freely, passion, peace, perfect, active, fun, playful, advantage, adventure, affection, gentle, pleasant, please, popular, positive, glad, precious, gladly, glamor, pretty, pride, glory, prize, good, profit, award, awesome, ready, beloved, relax, benefit, grand, relief, respect, great, vigor, best, haha, romantic, brave, handsome, safe, bright, happy, calm, harmless,scrumptious, care, heartfelt, sentimental, heartwarming, share, heaven, helpful, hero, smart, charm, honest, cheer, honor, strong, succeed, sunnier, confidence, hug, sunshine, considerate, humor, sweetheart, daring, sweetly, dear, kind, thanked, kiss, thoughtful, triumph, lovely, useful, enjoy, loves, value, okay, wisdom, wow, outgoing, paradise, etc.
Negative Emotion	Abandon, snob, abuse, madder, sob, envious, envy, afraid, exhaust, mess sorrow, fail, sorry, fake, stank, agony, fear, alone, mistake, anger, fearful, strain, strange, annoy, stress, stubborn, moody, stupid, fool, forbid, murder, submissive, suck, assault, frantic, sucked, attack, neglect, nerd, avoid, fuck, nervous, suffer, awful, neurotic, awkward, bad, bashful, obsess, fume, offense, offend, overwhelm, temper, pain, bore, goddam, tense, gossip, grave, broke, greed, grief, panic, terrified, burden, careless, terrify, complain, thief, contempt, threat, crap, enemy, lying, smother, yearn, mad, smug, etc.
Anger	Abuse, jealous, jerked, kill, anger, mad, mock, beaten, brutal, danger, prick, defense, protest, destroy, punish, destruct, rage, resent, enemy, revenge, rude, envy, shit, fuck, stubborn, furious, tantrum, hateful, vicious, victim, hell, violent, war, warfare, idiot, interrupt, weapon, wicked, etc.
Anxiety	Afraid, alarm, anguish, avoid, awkward, discomfort, distract, distress, disturb, doubt, dread, dwell, embarrass, emotional, fear, frantic, fright, guilt, irrational, nervous, overwhelm, panic, repress, restless, rigid, risk, scare, shake, shame, shook, shy, strain, stunned, tense, terrify, turmoil, upset, uptight, etc.

Appendix D: Official response from yelp


GC
Grace Chu <gchu@yelp.com>
昨天, 23:43
LI, Aaron [Student]

Aaron,

Our definitions for "useful" and "cool" are more or less the same as the universal definitions for those two words. "Useful" means that the information presented is beneficial and helpful - the information provided is something other people can use or depend on to formulate their decisions or shape their experiences. "Cool" can mean various things, but generally it usually means that something is attractive, impressive, trendy, great, awesome, or even used to express approval or admiration.

We cannot provide you the view count of a review - this is not something we have available at the moment.

Thanks,
Grace

Appendix E1: Using yelp tenure to measure reviewer expertise

Variables	NB model estimating no. of useful votes			
	Model 1	Model 2	Model 3	Model 4
Model 1: Control effects				
Rating	–0.5732***	–0.5538***	–0.5602***	–0.5628***
Squared rating	0.0653***	0.0684***	0.0696***	0.0702***

(*continued on next page*)

(*continued*)

Variables	NB model estimating no. of useful votes			
	Model 1	Model 2	Model 3	Model 4
Length	0.0002	0.0002	0.0002	0.0002
Anger	0.0040	0.0237	0.0243	0.0264
Anxiety	0.0290	0.0156	0.0191	0.0237
Positivity	–0.0063	–0.0024	–0.0024	–0.0023
Negativity	0.0181	0.0090	0.0092	0.0079
Readability	0.0023	0.0028	0.0027	0.0027
Log (review age)#	1	1	1	1
Reviewer status	1.0013***	0.9637***	0.9599***	0.9638***
Reviewer average rating	0.0530	0.0486	0.0506	0.0496
Restaurant reputation	0.3096***	0.2367***	0.2346***	0.2340***
Restaurant popularity	0.0000	0.0001	0.0001	0.0001
Restaurant age	–0.0012***	–0.0010***	–0.0010***	–0.0010***
Price: $	–0.0105	–0.0659	–0.0944	–0.1047
Price: $$	0.1582	0.1466	0.1163	0.1055
Price: $$$	0.2225	0.1094	0.0785	0.0610
Price: $$$$	0.0000	0.0000	0.0000	0.0000
Reviewer review count	0.0018***	0.0001	0.0005**	0.0005**
Model 2: Linear effects				
Review Certainty		0.0101	0.0151	0.0139
Reviewer Expertise		0.0000	–0.0000	0.0000
(Reviewer Yelp tenure)				
Reviewer popularity		0.0165***	0.0153***	0.0161***
Restaurant niche width		–0.0649**	–0.0641**	–0.0630**
Model 3: two-way interaction effects				
Certainty*expertise (**H1**)			–0.0000	–0.0000
Certainty*popularity (**H2**)			–0.0027**	–0.0030**
Certainty*niche width				0.0086
Expertise*popularity				–0.0000
Expertise* niche width				–0.0003
Popularity* niche width				–0.0000
Model 4: three-way interaction effects				
Certainty*expertise*niche width (**H3**)				–0.0001
Certainty*popularity*niche width (**H4**)				0.0026*

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.
#As suggested by Allison (1999), we included the natural log of the review age as a predictor with regression coefficient equal to 1 with the purpose of incorporating variable observation periods while maintaining the Poisson error structure of the data.

Appendix E2: Using elite's status to measure reviewer expertise

Variables	NB model estimating no. of useful votes			
	Model 1	Model 2	Model 3	Model 4
Model 1: Control effects				
Reviewer's review count	0.0029**	0.0005**	0.0006	–0.0001
Rating	–0.2444**	–0.4954***	–0.5062***	–0.5817***
Squared rating	0.0251	0.0611***	0.0629***	0.0720***
Length	0.0001	0.0002	0.0002	0.0002
Anger	0.0349	0.0231	0.0239	0.0199
Anxiety	–0.0109	0.0045	0.0080	0.0162
Positivity	–0.0051	–0.0026	–0.0026	–0.0032
Negativity	0.0084	0.0092	0.0097	0.0116
Readability	0.0025	0.0027	0.0025	0.0030
Log (review age)#	1	1	1	1
Reviewer Yelp tenure	–0.0001	0.0000	–0.0000	0.0001
Reviewer average rating	0.1031***	0.0577	0.0599*	0.0584
Restaurant reputation	0.1753***	0.1938***	0.1914***	0.2134***
Restaurant popularity	–0.0000	0.0000	0.0000	–0.0000
Restaurant age	–0.0009***	–0.0010***	–0.0009***	–0.0010***
Price: $	–0.0343	–0.0079	–0.0424	0.1033
Price: $$	0.1793	0.1916	0.1544	0.2828
Price: $$$	0.1980	0.1208	0.0900	0.1855
Price: $$$$	0.0000	0.0000	0.0000	0.0000
Model 2: Linear effects				
Review certainty		0.0082	0.0170	0.0139
Reviewer expertise		0.8846***	0.8830***	0.9151***
(Elite status)				
Reviewer popularity		0.0152***	0.0138***	0.0748***
Restaurant niche width		–0.0664**	–0.0652**	–0.0701**
Model 3: Two-way interaction effects				
Certainty*expertise (**H1**)			–0.0131	–0.0042
(Certainty*elite status)				
Certainty*popularity (**H2**)			–0.0027**	–0.0034***
Certainty*niche width				0.0128

(*continued on next page*)

(*continued*)

Variables	NB model estimating no. of useful votes			
	Model 1	Model 2	Model 3	Model 4
Popularity* niche width				–0.0015
Expertise* niche width				0.0137
(Elite status*niche width)				
Expertise*popularity				–0.0600***
(Elite status*popularity)				
Model 4: Three-way interaction effects				
Certainty*expertise*niche width (**H3**)				–0.0108
(Certainty*elite status*niche width)				
Certainty*popularity*niche width (**H4**)				0.0024

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

Appendix E3: Using review rating to measure reviewer expertise

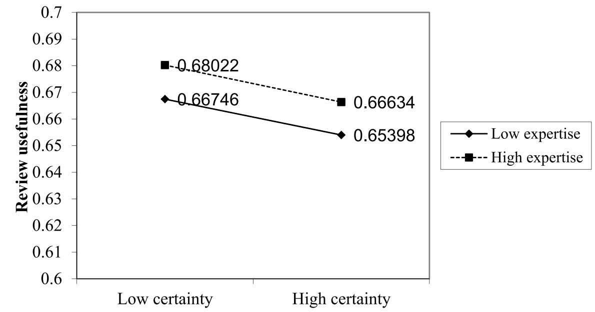
Variables	NB model estimating no. of useful votes			
	Model 1	Model 2	Model 3	Model 4
Model 1: Control effects				
Reviewer's review count	0.0016***	0.0008***	0.0008***	0.0007***
Elite Status	0.9986***	1.0113***	1.0067***	1.0100***
Squared rating	–0.0155***	0.0732***	0.0741***	0.0758***
Length	0.0001	0.0001	0.0002	0.0002
Anger	0.0182	0.0233	0.0246	0.0260
Anxiety	–0.0057	0.0016	0.0050	0.0087
Positivity	–0.0050	–0.0032	–0.0031	–0.0031
Negativity	0.0179	0.0116	0.0120	0.0101
Readability	0.0025	0.0025	0.0024	0.0024
Log (review age)#	1	1	1	1
Reviewer Yelp tenure	–0.0001	0.0001	0.0001	0.0001
Reviewer average rating	0.0141	0.0502	0.0525	0.0487
Restaurant reputation	0.2587***	0.2485***	0.2449***	0.2431***
Restaurant popularity	–0.0001	–0.0001	–0.0001	–0.0001
Restaurant age	–0.0010***	–0.0011***	–0.0010***	–0.0011***
Price: $	–0.2178	–0.0159	–0.0507	–0.0493
Price: $$	0.0321	0.1764	0.1396	0.1394
Price: $$$	0.0431	0.1389	0.1027	0.0999
Price: $$$$	0.0000	0.0000	0.0000	0.0000
Model 2: Linear effects				
Review certainty		0.0101	–0.0099	–0.0124
Reviewer expertise		–0.6063***	–0.6108***	–0.6185***
(review rating)				
Reviewer popularity		0.0122***	0.0114***	0.0143
Restaurant niche width		–0.0651**	–0.0644**	0.0358
Model 3: Two-way interaction effects				
Certainty*expertise **(H1)**			0.0068	0.0073
(Certainty*review rating)				
Certainty*popularity **(H2)**			–0.0027**	–0.0026**
Certainty*niche width				0.0339
Popularity* niche width				0.0000
Expertise* niche width				–0.0271
(review rating*niche width)				
Expertise*popularity				–0.0005
(review rating*popularity)				
Model 4: Three-way interaction effects				
Certainty*expertise*niche width **(H3)**				–0.0060
(Certainty*review rating*niche width)				
Certainty*popularity*niche width **(H4)**				0.0022*

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

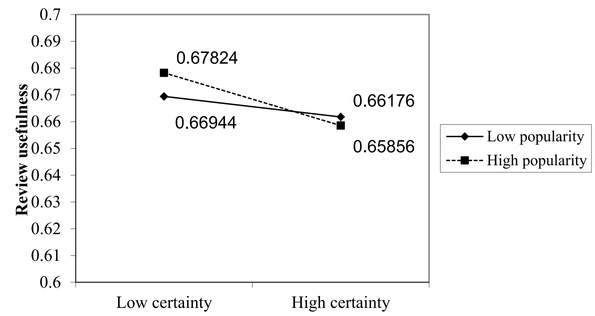
Appendix F: The plots of our interaction effects

Panel A: The two-way interaction between certainty and expertise (H1)[9]

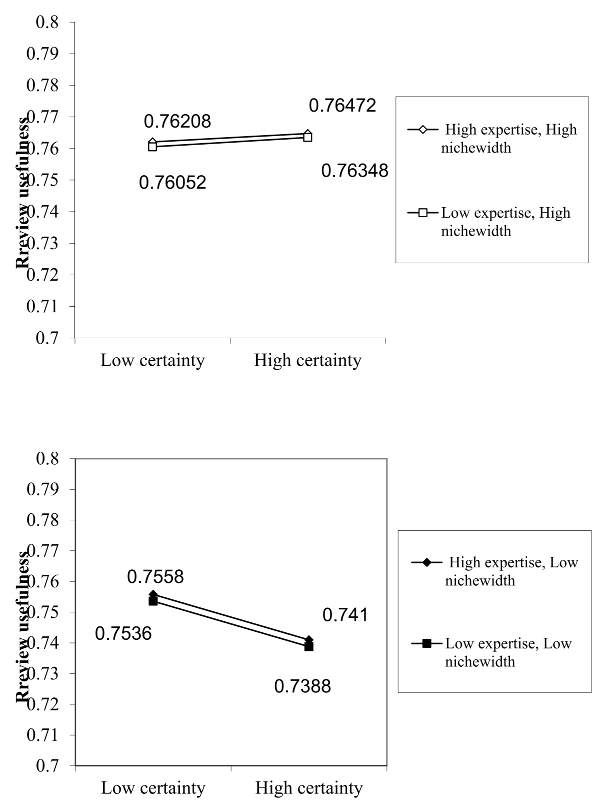
[9] The *paralleled* lines in Panel A are consistent with our empirical findings that H1 was *not* supported. We have discussed the reason for the insignificant results (see pp. 32–33).



Panel B: The two-way interaction between certainty and popularity (H2)

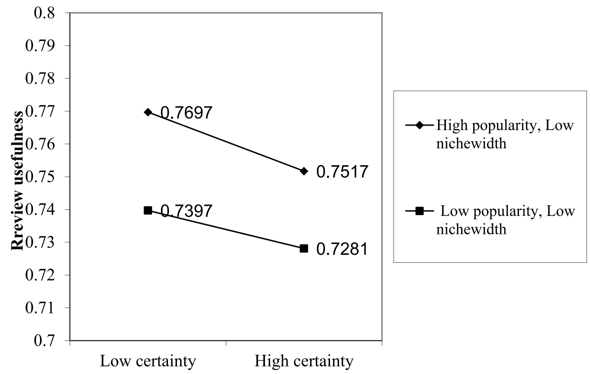


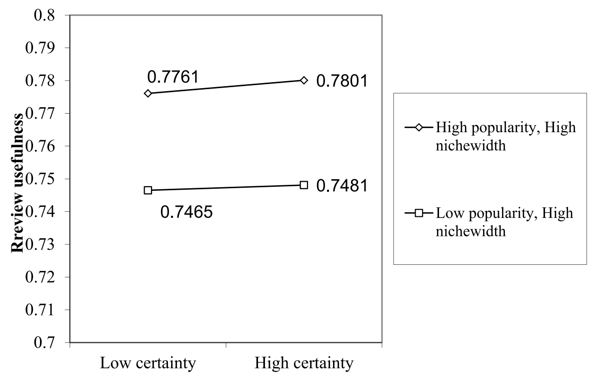
Panel C: The three-way interaction between certainty, expertise, and niche width (H3)[10]



Panel D: The three-way interaction between certainty, popularity, and niche width (H4)

[10] Regarding the *seemingly paralleled* lines in Panel C, we note that the three-way interaction effect among review certainty, reviewer expertise, and restaurant niche width is statistically significant ($\beta = -0.0003$, $p < 0.01$; as shown in our main results in Table 7), but may not be economically significant. The coefficient (–0.0003) implies that each unit change of the three-way-interaction term leads to 0.03% unit change of usefulness, which is relatively small in magnitude to be observed by eyes in the slopes of the plots.





Appendix G: Empirical comparisons among standard poisson, nb, zip and zinb for three-way interactions

Variables	Zero-Inflated Negative Binomial (ZINB)	Standard Poisson	Negative Binomial (NB)	Zero-Inflated Poisson (ZIP)
Rating	–0.5416***	–0.5094***	–0.6268***	–0.4060***
Squared rating	0.0692***	0.0595***	0.0733***	0.0494***
Length	0.0002	0.0001	0.0002	–0.0001
Anger	0.0248	–0.0271	0.0256	–0.0376
Anxiety	–0.0033	–0.0159	0.0015	–0.0483
Positivity	–0.0033	0.0000	–0.0040	0.0024
Negativity	0.0063	0.0302*	0.0083	0.0463**
Readability	0.0027	0.0017	0.0029	–0.0001
Log (review age)#	1	1	1	1
Reviewer Status	0.4584***	0.8859***	0.6536***	0.5366***
Reviewer Yelp Tenure	–0.0001	0.0004***	0.0001	0.0003**
Reviewer average rating	0.0606*	0.0257	0.0408	0.0591*
Restaurant reputation	0.1578**	0.2635***	0.2840***	0.1727***
Restaurant popularity	0.0001	–0.0002	0.0000	–0.0003*
Restaurant age	–0.0010***	–0.0011***	–0.0013***	–0.0007***
Price: $	–0.1592	–0.0487	–0.1034	–0.1391
Price: $$	0.0290	0.1546	0.0859	0.0389
Price: $$$	–0.0145	0.0666	0.1304	–0.1035
Price: $$$$	0.0000	0.0000	0.0000	0.0000
Review certainty	0.0149	0.0021	0.0176	0.0029
Reviewer expertise	0.0011***	0.0010***	0.0012***	0.0012***
Reviewer popularity	0.0430***	0.0214***	0.0430***	0.0178***
Restaurant niche width	–0.0679***	–0.0620***	–0.0652**	–0.0470**
Certainty*expertise (**H1**)	–0.0001	–0.0000	–0.0001	–0.0001
Certainty*popularity (**H2**)	0.0016	–0.0006*	0.0015	–0.0004
Certainty*niche width	0.0184	0.0125	0.0170	0.0160
Expertise*popularity	–0.0000***	–0.0000***	–0.0000***	–0.0000***
Expertise* niche width	–0.0000	–0.0001	–0.0000	–0.0002**
Popularity* niche width	0.0011	0.0008*	0.0011	0.0012**
Certainty*expertise*niche width (**H3**)	–0.0003*	–0.0001	–0.0003**	–0.0001
Certainty*popularity*niche width (**H4**)	0.0058**	0.0012***	0.0058***	0.0012***
Goodness-of-fit index AIC (smaller is better)	20,690.6691	23,681.7482	20,949.7221	22,215.1408
Goodness-of-fit index BIC (smaller is better)	21,085.9637	23,897.3634	21,172.5245	22,517.0021

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

#As suggested by Allison (1999), we included the natural log of the review age as a predictor with regression coefficient equal to 1 with the purpose of incorporating variable observation periods while maintaining the Poisson error structure of the data.

Appendix H. Summary of relevant studies on cognitive effort

Article	Focus	Findings	Method
[70]	Perceived cognitive effort	The discrete emotions in a review affect reader perceptions of reviewers' cognitive effort.	Laboratory experiments
[51]	Perceived cognitive effort	More cognitive effort is involved with the message containing high-quality arguments.	Laboratory experiments
[12]	Perceived cognitive effort	Reviews with negative emotions are perceived to be more reviewer's cognitive efforts than positive emotions.	Laboratory experiments
[37]	Expenditure of cognitive effort	Anger influences how much cognitive effort people expend in processing the stimuli they confront.	Theoretical analysis
[18]	Anticipated cognitive effort	Time requirements and error-likelihood are two potential determinants of effortfulness.	Laboratory experiments
[8]	Need for cognition	Individuals high in need for cognition are likely to be involved in message processing and persuasion.	Laboratory experiments
[20]	Expenditure of cognitive effort	Individuals less prefer more effortful choices than those that are less effortful.	Laboratory experiments

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