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Effects of conflicting aggregated rating on eWOM review credibility and diagnosticity: The moderating role of review valence

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ABSTRACT

Most B2C websites provide consumers with two types of electronic Word-of-Mouth (eWOM) information, namely aggregated rating and individual review. The present research investigates the effects of a conflicting aggregated rating on the perceived credibility and diagnosticity of individual reviews. The results of our laboratory experiment demonstrate that the presence of a conflicting aggregated rating will decrease review credibility and diagnosticity via its negative effect on consumers' product-related attributions of the review. In addition, these effects are more salient for positive reviews than for negative ones. These findings contribute to a better understanding of the interactions between different types of eWOM information and provide practitioners with actionable suggestions on how to improve the design of their eWOM systems.

1. Introduction

The importance of electronic word-of-mouth (eWOM) as a new element of the marketing communications mix has been well recognized [9,13,27]. Online retailers such as Amazon.com and third-party infomediaries such as Epinions.com invite consumers to rate the product they have purchased and share their shopping experiences with others through customer reviews. In addition, they provide an aggregated rating for each product based on all reviewers' input to facilitate a quick and overall impression of the product. This is a unique feature of eWOM systems because in traditional WOM communications it is almost impossible to sort out all of the communicators' opinions and obtain a summarized product evaluation. While aggregated rating and individual review are supposed to work together to constitute an online persuasive environment, most previous research investigated these two types of eWOM information separately [11,16,27,50], and the interactions between them have been largely underexplored. Consider the example in Fig. 1. It is not unusual that a particular review would conflict with an aggregated rating in terms of valence (in this case, the review is unfavorable while the aggregated rating is positive). In this situation, will the presence of a conflicting aggregated rating influence consumers' adoption intention toward the review? If yes, will it be increased because "truth always rests with the minority"? Or, will it be decreased because the review is at odds with the majority opinion? Unfortunately, the extant literature does not provide explicit answers to these questions and inconsistent views exist on whether or not a conflicting aggregated rating will influence review adoption.

On the one hand, early research on social cognition shows that when making judgments people tend to underuse base-rate information (e.g., aggregated ratings) and rely almost exclusively on individuating information (e.g., individual reviews) if both types of information are available [6,30,38,46]. According to this line of research, one might expect that the presence of a conflicting aggregated rating has little impact on review adoption. In contrast, recent studies on eWOM have demonstrated that aggregated ratings have significant influences on consumers' purchasing decisions [11,58]. Most notably, Cheung et al. [10] found that recommendation consistency, which refers to the evaluative consistency between a particular review and other reviews, was positively related to consumers' credibility perception and adoption intention of the target review. These results suggest that the presence of a conflicting aggregated rating may influence consumers' review adoption.

The present research aims to reconcile the inconsistent findings by proposing review valence as a moderator and to identify the underlying mechanisms from an attribution perspective. Attribution is

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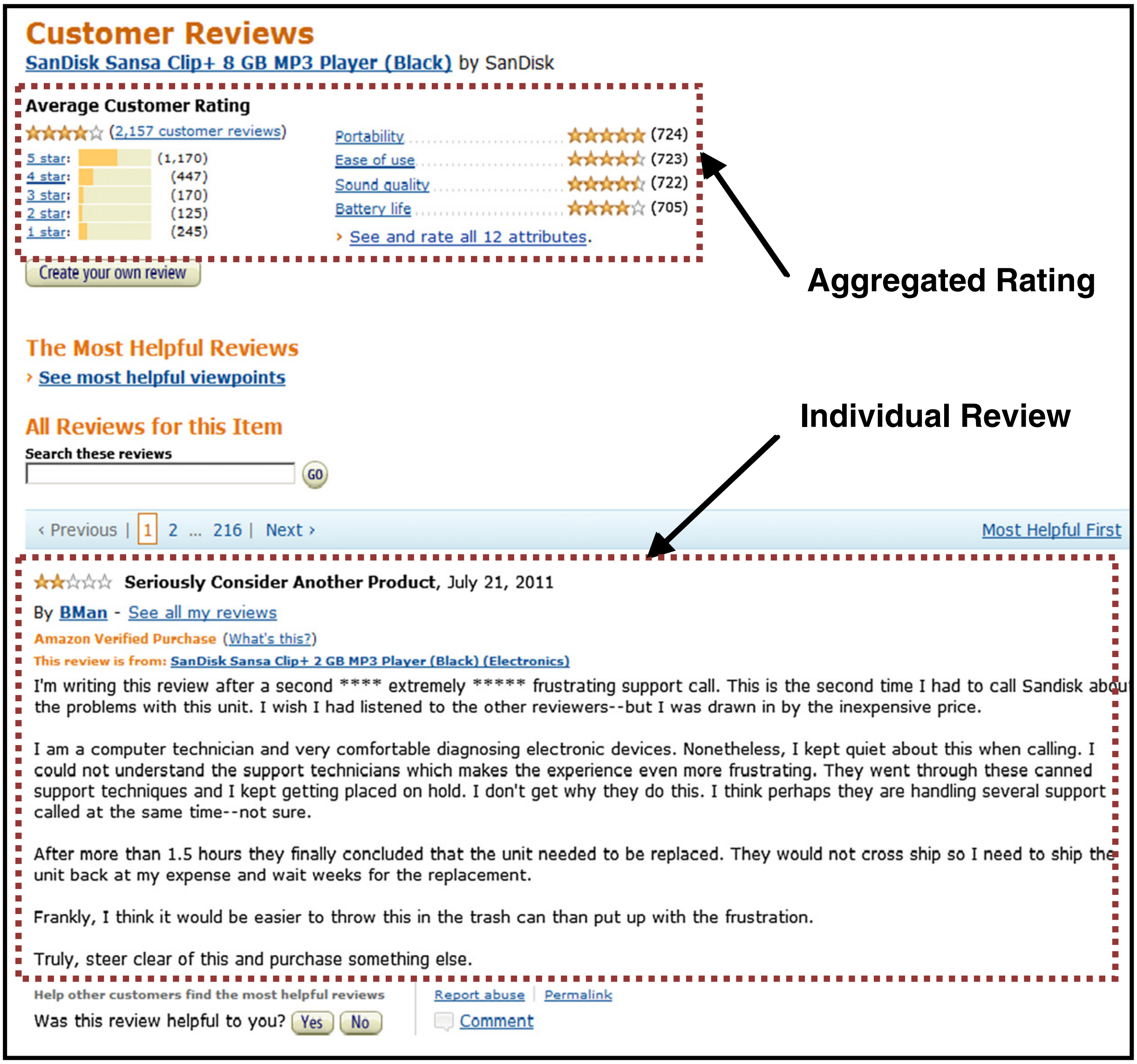

Fig. 1. An example of the eWOM system on Amazon.com.

a motivational, perceptual, and cognitive process in which people use prior knowledge and present information to make causal inferences [32]. Researchers have long noted that understanding consumers' perceptions of cause-and-effect relationships is central to the knowledge of consumer behavior [21,42,71]. In the eWOM literature, however, the attribution approach has not received adequate attention. Only a few studies have adopted attribution theory to explain consumers' responses to eWOM messages [8,57,58], and empirical investigations on consumers' attributional thinking of eWOM are still scarce. Thus it is imperative to study the role of attribution in consumers' review adoption process. Toward this end, the present research investigates how the presence of a conflicting aggregated rating influences perceived credibility and diagnosticity of an individual review, which are the two most important determinants of review adoption [10,44,55,67]. In addition, we test the moderating role of review valence and the mediating role of consumer attribution in these effects. A laboratory experiment was conducted to examine the proposed effects and supportive evidence was obtained.

To the best of our knowledge, this research is the first one that focuses on the conflict between aggregated rating and individual reviews and investigates its consequences from an attribution perspective. We suggest a moderator to resolve the controversies regarding whether or not the review-rating conflict will influence review adoption and identify the mechanisms underlying this moderating effect. Beyond theoretical contributions, our findings can also extend the practitioners' knowledge of the interactions between different types of eWOM information, which will help them improve the design of their eWOM systems. Therefore, this research has important implications for both eWOM research and managerial practice.

The paper proceeds as follows: Section 2 reviews the related literatures and develops the theoretical framework and hypotheses for this research. Sections 3 and 4 describe the experiment and its results. Finally, Section 5 discusses the theoretical and managerial implications of our findings and Section 6 concludes by pointing out the possible future research directions.

2. Research framework and hypotheses

2.1. Research overview

As human beings search for an understanding of and hence some control over the environment, they attempt to explain the causes of events and outcomes [25,35]. For WOM communications in both online and offline settings, consumers also concern themselves with explanations—why this particular WOM message has emerged and why the communicator has told me this [37,41,57]. Thus attribution is a spontaneous reaction when consumers are reading WOM reviews.

According to attribution theory, different causes can be inferred from a single event or outcome. However, people usually organize their attributional thinking along a few key dimensions [26,70,73]. Of them, *locus* is the most fundamental and central dimension [33,40,69]. Locus of attribution is defined as the source of the cause; that is, who shall take the responsibility for an outcome [69]. Previous research has shown that attribution locus has a significant impact on people's responses to the event or outcome being explained [34,69]. Therefore, it is the focus of this research. We operationalize locus as a continuum with product-related causes and non-product-related causes being the two endpoints. In other words, consumers' attribution of an individual review is measured in terms of the extent to which the content of the review is caused by actual product performance or by non-product-related factors such as the reviewer's inappropriate usage or his hidden motives behind intentional bragging or faultfinding [57].

Building upon attribution theory [35,42,69] and the eWOM literature [10,49,57,58], we propose that the presence of a conflicting aggregated rating will reduce consumers' product-related attributions of the individual review, which in turn, leads to decreased review credibility and diagnosticity. Furthermore, the effect of the conflicting aggregated rating on consumer attribution is moderated by review valence. We summarize the research framework and hypotheses in Fig. 2.

2.2. Effect of conflicting aggregated rating on review attribution

In attribution theory, *consensus* is defined as the extent to which a person's responses to a certain stimulus on a particular occasion are similar to others' responses [32]. A high consensus occurs if the person responds to the stimulus in the same way as others, while a low consensus results from a disagreement between the person's responses and others'. Based on this conceptualization, Kelly [32,34] argues that when people are explaining a person's responses to a stimulus, their attribution outcomes will be influenced by the information of consensus. Specifically, a higher consensus indicates that the stimulus evokes more similar responses across different people. Therefore, it will lead to more attributions to the stimulus, that is, people believe that the target person's responses are mainly caused by the stimulus rather than other non-stimulus-related reasons. This argument has been further corroborated by subsequent empirical studies [23,39,72].

In the eWOM context, an aggregated rating reflects all reviewers' average product evaluation. Hence, the conflict with the aggregated rating implies a low consensus in product evaluation between the particular reviewer and others. In other words, the reviewer responds to the product (i.e., the stimulus) differently than do others. Based on Kelley's arguments on consensus [32], it is reasonable to predict that, by making the information of a low consensus salient, the presence of a conflicting aggregated rating will decrease consumers' product-related attributions of the review. Based on this discussion, we hypothesize that:

H1. Consumers are less likely to make product-related attributions of the individual review when a conflicting aggregated rating is present than it is not.

2.3. Moderating effect of review valence on review attribution

People differ in their causal attributions of positive and negative information [41]. Because social norms in general encourage positive comments about people or objects, positive information appears to be consistent with social norms while negative information appears to be inconsistent [18,31]. As a result, people are less likely to make stimulus-related attributions for positive information because it can also be explained by other plausible causes, such as social norms and peer pressure. In contrast, when dealing with negative information, which is socially undesirable, people have more confidence in ruling out non-stimulus causes and attribute it to the stimulus itself [29,41].

The differences in attributions for positive versus negative information might be more salient for eWOM reviews. According to attribution theory, attribution is a motivational process and its outcomes are largely affected by personal motivations such as self-protection and self-esteem [35]. For example, consumers are more likely to make product-related attributions for product failure than vendors do [22]. Similarly, decision makers tend to attribute unsuccessful decisions to the situation and take personal credit for successful ones [12,43]. In online settings, the volatile nature of online identities increases consumers' concerns regarding the authenticity of eWOM reviews, which will drive consumers to make causal inferences in a self-protecting manner. Consequently, they tend to make product-related attributions for negative reviews and non-product attributions for positive ones so as to minimize risk and avoid potential losses [57].

An important implication of such differences is that the presence of a conflicting aggregated rating may have differential impacts on consumers' attributions of positive versus negative reviews. Previous research on confirmation bias shows that people seek and interpret evidence in ways that are consistent with the existing beliefs,

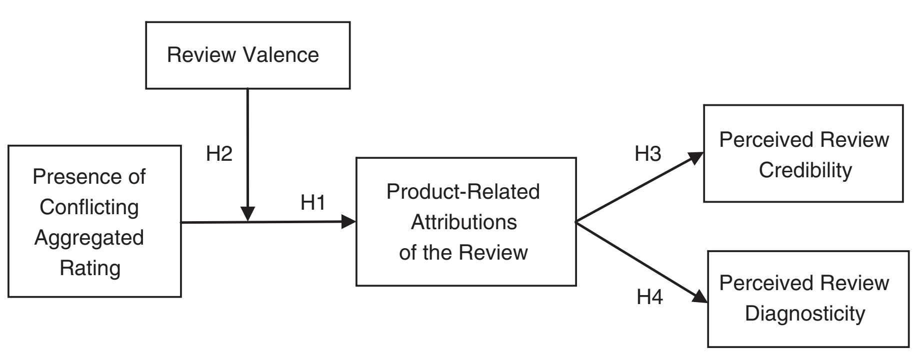

Fig. 2. Research framework and hypotheses.

expectations, or hypotheses at hand. For inconsistent evidence, however, people tend to ignore or underutilize them [45]. As discussed before, when the individual review is positive, consumers are more likely to believe that it is due to non-product-related reasons. From the consumers' point of view, the presence of a conflicting (i.e., negative) aggregated rating provides evidence for their existing beliefs. Therefore, their tendency to make non-product-related attributions will be further enhanced. In contrast, when the individual review is negative, consumers tend to make product-related attributions. In this case, the presence of a conflicting (i.e., positive) aggregated rating, which is related to non-product-related attributions, is inconsistent with the consumers' prior beliefs. To resolve this inconsistency, consumers are likely to downplay the aggregated rating, leading to a less salient effect of this information on their causal inferences of the review. Accordingly, we predict that consumers will be more vulnerable to the conflicting aggregated rating when making attributions for a positive review than for a negative one. Based on this discussion, we hypothesize that:

H2. The effect of the presence of a conflicting aggregated rating on consumers' review attribution is more salient for positive reviews than for negative ones.

2.4. Effect of review attribution on perceived review credibility

In contrast to traditional WOM communications that are transmitted through one's immediate contacts [7], the Internet connects a mass of unacquainted users and allows them to express feelings and opinions without disclosing their real identities [13]. As a result, the authenticity of an eWOM review is uncertain, making its credibility a critical determinant of whether or not the review shall be accepted or rejected [10,67].

Credibility is defined as the extent to which a piece of information is perceived as true and valid [65]. The effect of attribution on information credibility has long been recognized. For example, Settle and Golden [59] as well as Smith and Hunt [62] showed that consumers who attribute a product claim to the actual characteristics of the product will rate the claim as more truthful than those who attribute the claim to the firm's desire to sell the product. In addition, Mizerski [40] suggests that consumers will perceive a piece of product information as accurate if they believe that the content of the information is caused by the product being described.

In the same vein, we argue that consumers' attributional thinking of an eWOM review will affect their perceptions of the review's credibility. Specifically, when an eWOM review is attributed to non-product-related causes, consumers will have less confidence in the reviewer's expertise and/or integrity. For example, the non-product-related causes for a negative review can be either the reviewer's inappropriate usage of a well-performing product or the intentional denigration from a competitor. Meanwhile, a positive review may be caused by non-product-related reasons such as the reviewer's inability to identify the product's deficiencies or some undercover motives for product promotion. In both cases, the reviewer's expertise or integrity is more or less suspicious, which decreases the perceived credibility of the reviewer as an information source [65]. Since information credibility is positively related to source credibility [56,68], we predict that perceived credibility of the eWOM review will also decrease as the result of the non-product-related attributions. On the other hand, when consumers attribute the eWOM review to product-related causes, i.e., they believe that the review information is indeed relevant to the product being described, they will perceive the reviewer and thereby the review as being credible [10,53,67]. Based on this discussion, we hypothesize that:

H3. Consumers' product-related attributions of an individual review have a positive effect on their perceptions of review credibility.

2.5. Effect of review attribution on perceived review diagnosticity

Diagnosticity is defined as the sufficiency of a piece of information for someone to arrive at a solution for a judgment task (e.g., judgment and categorization) [19,36]. It is determined by the perceived correlation between the information and the judgment task and is often operationalized as the information's helpfulness and usefulness for making a judgment in empirical studies [14,60]. Previous research on information processing has noted that the likelihood that a piece of information will be used for judgment is a positive function of its diagnosticity [19]. Therefore, perceived diagnosticity is an important determinant of review adoption [67].

In the eWOM literature, researchers basically agree that an eWOM review will be perceived as diagnostic if it can facilitate consumers' product evaluation prior to purchase [28,44]. According to this conceptualization, we argue that the product-related attributions of an eWOM review will positively influence its perceived diagnosticity. This is because product-related attributions enable consumers to obtain information pertaining to the characteristics of the product, which is helpful for them to judge its performance before purchase. In contrast, when the review is attributed to non-product-related causes, it reveals little information about the product itself. Hence, consumers will perceive the review as less relevant and, consequently, less diagnostic for product evaluation [57]. Based on this discussion, we hypothesize that:

H4. Consumers' product-related attributions of an individual review have a positive effect on their perceptions of review diagnosticity.

3. Research method

3.1. Experimental design

A 2 (conflicting aggregated rating: without vs. with) × 2 (review valence: positive vs. negative) × 2 (review extremity: low vs. high) full-factorial between-subjects design was employed to test our hypotheses, which produced eight conditions (as shown in Table 1). Previous research has revealed an extremity bias in impression and evaluation formation, which indicates that extreme information has greater weight than moderate information [61]. Therefore, it is worthwhile to examine whether or not our hypotheses are generalizable to both moderate and extreme individual reviews by including the factor of review extremity.

3.2. Experimental stimuli

For each experimental condition, we created a graphical image, which looked like a screenshot captured from a real online review website. To reduce the influences of brand name and price on the

Table 1
Experimental design.

		Review valence and extremity			
		Positive		Negative	
		Moderate	Extreme	Moderate	Extreme
Conflicting aggregated rating	*Without*	Group 1	Group 2	Group 3	Group 4
	With	Group 5	Group 6	Group 7	Group 8

participants' review perceptions, we blurred that information using Adobe Photoshop filter-glass tools.

We selected multimedia speakers as the target product for the experiment, mainly because of its experiential nature. Prior research has demonstrated that consumers tend to rely more on word-of-mouth communications to make purchase decisions for experience products than for search products [49]. In addition, as multimedia speakers are commonly used as a peripheral device for computers, most consumers can comprehend the review contents based on their own experiences.

For the manipulation of aggregated rating, a rectangular zone with a summarized score was clearly visible to the subjects in the with-rating conditions. In the without-rating conditions, to ensure that the information of aggregated rating is completely illegible while keeping the image size and page layout exactly the same across all experimental conditions, we masked that rectangular zone with a banner ad and then blurred it with Adobe Photoshop filter-glass tools. Regarding its valence, we selected two stars and four stars (out of five stars[1]) to represent a negative and a positive rating respectively. We avoided using one star and five stars for aggregated rating because of a concern on the perceived realism of the stimuli. Being the endpoints of a five-point scale, an aggregated rating of one star (or five stars) would imply that almost all reviewers have unanimously voted one star (or five stars), which is not very common in the real world. In addition, we conducted a pretest to identify the proper total number of reviews to make the sample representative and hence the aggregated rating meaningful.[2] In this pretest, 58 subjects were asked to estimate the minimal sample size that was considered as being adequately representative when consumers were looking for the aggregated rating of a product on the Internet. The answers varied from 10 to 200 (Mean = 70) and more than 90% of the respondents suggested a number below 96. Therefore, 96 was selected as the total number of reviews and placed next to the aggregated rating.

The review valence was manipulated by varying both the star rating and the textual content of the target review. Specifically, a one-star rating and a two-star rating (out of five stars) were used to signify an extremely negative and a moderately negative review respectively, while a four-star rating and a five-star rating were used for a moderately positive and an extremely positive review. To ensure the relevance of the review texts, we first identified ten of the most frequently mentioned product attributes based on a large number of real-world online product reviews. Thirty subjects were then asked to rate the importance of each attribute for their purchasing decisions. Four of the most important attributes that scored more than five points on a seven-point scale were selected, after which four reviews (two positive and two negative) commenting on these four attributes were prepared. We further fine-tuned the review texts with a series of pretests until all reviews had the same length and were rated as equally comprehensible ($p > .05$). The webpage screenshots of selected experimental conditions are shown in Appendix A (Figs. A1–A4).

3.3. Measures

While a variety of measuring instruments have been proposed to assess the locus dimension of attribution, it was found that the rating scales have a better performance in both reliability and validity than others [17]. Accordingly, we measured the locus of attribution by asking participants to what extent they felt that the review reflected the characteristics of the product and to what extent they thought that the review content was derived from the product [40,54]. Perceived credibility was measured by three items adapted from Cheung et al.'s [10] study, and perceived diagnosticity was assessed in terms of perceived helpfulness of the review for consumer judgment and purchase decision [28,36]. All responses were recorded on seven-point semantic-pair scales.

In addition, we measured the participants' general attitude toward online product reviews [50] and their subjective product knowledge [20] as control variables. Responses were recorded on seven-point Likert scales (1 = "strongly disagree"; 7 = "strongly agree"). To check the manipulations of aggregated rating and review valence, subjects were also asked to recall the value of the aggregated rating (only for the with-rating conditions) and to rate the valence of the individual review (for all conditions). We listed all measurement items of the dependent and control variables in Appendix B.

3.4. Participants, incentives, and procedures

A total of 168 subjects participated in this study and received monetary compensation, which corresponds to 21 subjects per condition.[3] Participants were undergraduate and graduate students recruited through online and offline advertisements at a large public university.

The experiment was administered in a behavior lab during a 30-minute session for each participant. After reading and signing an "informed consent" form, participants were randomly assigned to one of the eight conditions. All experiment instructions, stimuli, and questionnaires were presented through a self-administered online survey system. To help participants become oriented to the survey system, a research assistant first asked them to complete an online questionnaire on their background information. They were then instructed to imagine that they wanted to buy a set of multimedia speakers for themselves and that they were searching for user-contributed reviews on the Internet. The stimulus image was then presented. Participants were told that it was a screenshot randomly captured from a real-world customer review website and that they needed to read the information on the webpage carefully.

After reading all the information on the stimulus image, participants were asked to respond to the measures of attribution as well as those of perceived credibility and diagnosticity of the review. To reduce the common method bias, these questions were separated by other questions that were relevant but of little interest to this research (e.g., questions about the argument strength and comprehensiveness of the review). The separation of measurement helps diminishing participants' ability and motivation to use their prior responses to answer subsequent questions, thus reducing consistency motifs and demand characteristics [51]. At the end of the questionnaire, participants answered several questions related to manipulation check and control variables. The self-administered survey system was programmed in such a way

[1] We used a five-star scale because it is used by most online retailers and third-party websites (e.g., Amazon.com, eBay.com, bestbuy.com, epinion.com, and yelp.com) for product ratings on their websites.

[2] It is possible that the effect size of aggregated rating is contingent upon the total number of reviews. However, as this study is the first attempt to explore the interactions between aggregated rating and individual reviews, we decided to keep this contextual factor constant and assign a relatively large figure as the number of total reviews so that it conforms to the classical definition of "base rate".

[3] The required sample size for an experiment is decided by four factors: 1) the research design; 2) the critical value for statistical significance (α); 3) the desired level of power ($1-\beta$); and 4) the estimated effect size [12]. Based on the empirical findings of prior eWOM studies [49,50], a medium effect size was assumed. According to the DF-ES-POWER-ALPHA table [12, pp. 311–314], a minimum number of 144 subjects (18 per condition) are required in order to ensure sufficient statistical power (power = 0.8) at the significance level of .05 for both main effects and interaction effects.

that 1) subjects needed to confirm that they had indeed read all of the information on the stimulus image before starting the questionnaire, and 2) once subjects had started the questionnaire, they could not go back and browse the stimulus image again. After completing all questions, participants were thanked, debriefed, and dismissed.

4. Results

4.1. Sample demographics and manipulation check

Among the 168 participants, 101 were male and 67 were female. Their average age was 22.7 years old. On average, the participants had used the Internet for 7.2 years and had spent approximately 28.9 h/week on the Internet. Most of them often read online reviews before making purchase decisions ($M = 6.40$, on a 7-point scale where 1 = "never" and 7 = "very often"). As the participants' demographic characteristics and Internet experience did not yield any significant effects on the dependent variables, they were omitted from further analyses.

Regarding manipulation check, the results reveal that all of the participants in the with-rating conditions read the aggregated rating information and could recall its score correctly. In addition, participants in the positive-review conditions rated the review as more favorable than those in the negative-review conditions ($M_{positive} = 5.14$ and $M_{negative} = -4.79$ on a 15-point scale where −7 = "very negative" and 7 = "very positive", $p < .001$). Therefore, our manipulations were successfully administered.

4.2. Results of hypotheses testing

The reliabilities of the measures were first examined. We calculated Cronbach's alpha for each construct and found that all of them met the benchmark of 0.70 [48] (as shown in Appendix B).

The group means and standard deviations of the three dependent variables are reported in Table 2. As we predicted main and interactive effects on multiple related dependent variables, a multivariate analysis of covariance (MANCOVA) was conducted [24], with the results presented in Table 3. Both the main effect of conflicting aggregated rating and its interaction with review valence are significant, suggesting that it is appropriate to test our hypotheses via univariate analysis of covariance (ANCOVA).

We then performed ANCOVA on review attribution to test H1 and H2, with the general attitude toward online reviews and subjective product knowledge as covariates. As shown in Table 4, the presence of a conflicting aggregated rating has a significant effect on participants' attributions of the individual review ($F(1, 158) = 14.891$, $p < .001$). Participants made fewer product-related attributions ($M = 4.39$) when the conflicting aggregated rating was present than when it was not ($M = 5.22$). In addition, the interaction between conflicting aggregated rating and review extremity is not significant ($F(1, 158) = .710$, $p = .547$), suggesting that this effect is not influenced by review extremity. Therefore, H1 is supported.

More importantly, we found a significant interaction between conflicting aggregated rating and review valence ($F(1, 158) = 13.047$, $p < .001$). Specifically, the presence of the conflicting aggregated rating negatively influences participants' product-related attributions of the review when the review is positive ($F(1, 78) = 35.31$, $p < .001$). However, when the review is negative, the conflicting aggregated rating has little impact on review attribution ($F(1, 78) = .617$, $p = .434$). Participants consistently ascribed the content of the review to product-related causes, regardless of its disagreement with the aggregated rating (see Fig. 3). Furthermore, the three-way interaction between aggregated rating, review valence, and review extremity is not significant ($F(1, 158) = 1.120$, $p = .292$), which suggests that review valence moderates the effect of conflicting aggregated rating on review attribution for both moderate and extreme reviews. These findings provide support for H2.

Recall that H3 and H4 predicate that the product-related attributions of the individual review have positive effects on its perceived credibility and diagnosticity. We performed regression analyses to test these hypotheses. The results show that, after controlling for the effects of general attitude toward online reviews and product knowledge, product-related attribution positively influences the review's perceived credibility ($ß = .707$, $p < .001$) and diagnosticity ($ß = .752$, $p < .001$). Therefore, H3 and H4 are both supported.

4.3. Post-hoc analyses for the mediating effects of review attribution

As we argued before, the presence of a conflicting aggregated rating would reduce consumers' product-related attributions of an individual review, which, in turn, would negatively influence its perceived credibility and diagnosticity. These arguments imply that

Table 3
MANCOVA results.

	Wilks' lambda	F	*p*-Value
Conflicting aggregated rating	.777	14.891	<.001
Review valence	.864	8.182	<.001
Review extremity	.945	3.004	.032
Conflicting aggregated rating × review valence	.870	7.782	<.001
Conflicting aggregated rating × review extremity	.987	0.710	.547
Review valence × review extremity	.961	2.119	.100
Conflicting aggregated rating × review valence × review extremity	.991	0.446	.721
Covariate: general attitude toward online reviews	.904	5.539	.001
Covariate: subjective product knowledge	.992	0.415	.742

Table 2
Descriptive statistics.

Experimental groups			Product-related attribution	Review credibility	Review diagnosticity
			Mean (*sd*)	Mean (*sd*)	Mean (*sd*)
Without conflicting aggregated rating	Positive review	4 stars	5.44 (*0.61*)	5.27 (*0.60*)	5.67 (*0.58*)
		5 stars	4.93 (*1.24*)	4.65 (*1.27*)	4.98 (*1.11*)
	Negative review	2 stars	5.02 (*1.18*)	4.68 (*1.10*)	5.14 (*1.20*)
		1 star	5.50 (*0.89*)	5.05 (*1.16*)	5.48 (*1.02*)
With conflicting aggregated rating	Positive review	4 stars	3.96 (*1.06*)	3.49 (*0.99*)	3.90 (*1.17*)
		5 stars	3.50 (*1.31*)	2.86 (*0.93*)	3.17 (*1.18*)
	Negative review	2 stars	5.17 (*1.07*)	4.72 (*0.97*)	5.20 (*1.16*)
		1 star	4.95 (*1.23*)	4.48 (*1.06*)	4.74 (*1.14*)

Table 4
ANCOVA results.

	Product-related attribution		Review credibility		Review diagnosticity	
	F	*p*-Value	F	*p*-Value	F	*p*-Value
Conflicting aggregated rating	22.439	<.001	40.662	<.001	39.908	<.001
Review valence	17.589	<.001	19.466	<.001	21.083	<.001
Review extremity	1.622	.205	5.037	.026	8.519	.004
Conflicting aggregated rating × review valence	13.047	<.001	22.123	<.001	18.147	<.001
Conflicting aggregated rating × review extremity	1.054	.306	1.312	.254	2.142	.145
Review valence × review extremity	3.711	.056	5.872	.017	5.167	.024
Conflicting aggregated rating × review valence × review extremity	1.120	.292	.718	.398	1.101	.296
Covariate: general attitude toward online reviews	2.863	.093	10.988	.001	15.479	<.001
Covariate: subjective product knowledge	.114	.737	.545	.462	1.072	.302

consumers' product-related attributions of the review mediate the effects of conflicting aggregated rating on review credibility and review diagnosticity. To test these mediation effects, we first performed ANCOVA on review credibility and review diagnosticity to explore whether or not the moderating effect of review valence on attribution would be transferred to credibility and diagnosticity perceptions.

As shown in Table 4, the ANCOVA results indicate that the presence of a conflicting aggregated rating has a negative effect on participants' credibility ($F(1, 158) = 40.662$, $p < .001$) and diagnosticity ($F(1, 158) = 39.908$, $p < .001$) perceptions of the review. Specifically, participants in the with-rating conditions rated the review as less credible and less diagnostic than those in the without-rating conditions (3.88 vs. 4.91 for credibility, 4.24 vs. 5.31 for diagnosticity). In addition, the moderating effects of review valence on review credibility ($F(1, 158) = 22.123$, $p < .001$) and diagnosticity ($F(1, 158) = 18.147$, $p < .001$) are both significant. As illustrated in Figs. 4 and 5, the presence of a conflicting aggregated rating decreases review credibility ($F(1, 78) = 67.685$, $p < .001$) and diagnosticity ($F(1, 78) = 58.218$, $p < .001$) for the positive review. However, both effects are not significant for the negative review (for credibility, $F(1, 78) = 1.109$, $p = .295$; for diagnosticity, $F(1, 78) = 2.134$, $p = .148$). These results provide preliminary evidence for the mediating role of review attribution.

Next, we formally examined the mediation effects following the procedures suggested by Baron and Kenny [4]. The regression analysis results in Table 5 show that the presence of a conflicting aggregated rating negatively influences review credibility ($p < .001$) and review diagnosticity ($p < .001$). As demonstrated before, the effects of review attribution on review credibility and diagnosticity are also significant. After review attribution was added to the regression model, however, the effect of conflicting aggregated rating became less salient. There results suggested that participants' product-related attributions of the review partially mediated the effects of conflicting aggregated rating on review credibility and diagnosticity.

Furthermore, we followed the procedure proposed by Preacher and Hayes' [52] and conducted the Sobel test [63] to test the significance of the mediation effects. Compared with the classic mediation-test

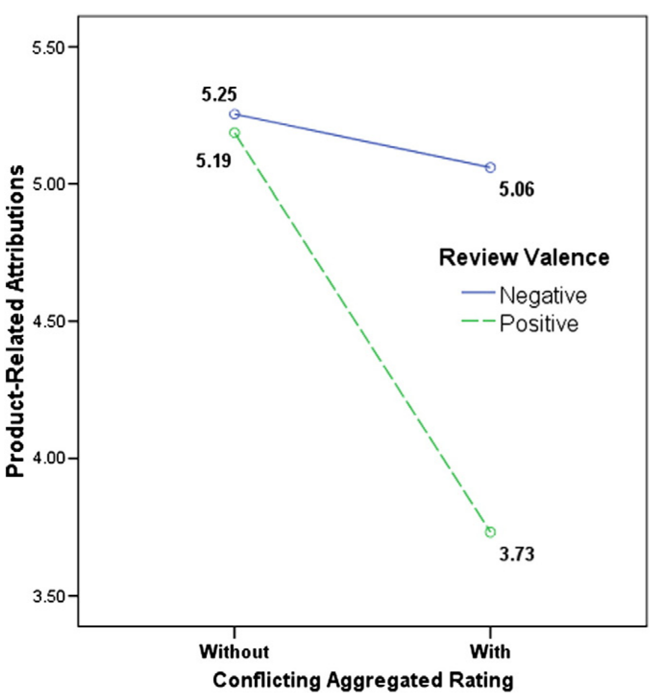

Fig. 3. Interaction between conflicting aggregated rating and review valence on review attribution.

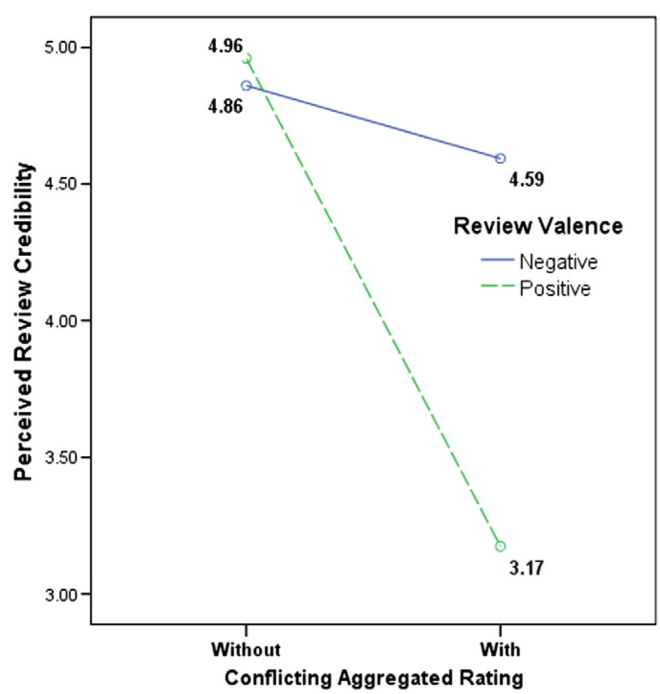

Fig. 4. Interaction between conflicting aggregated rating and review valence on review credibility.

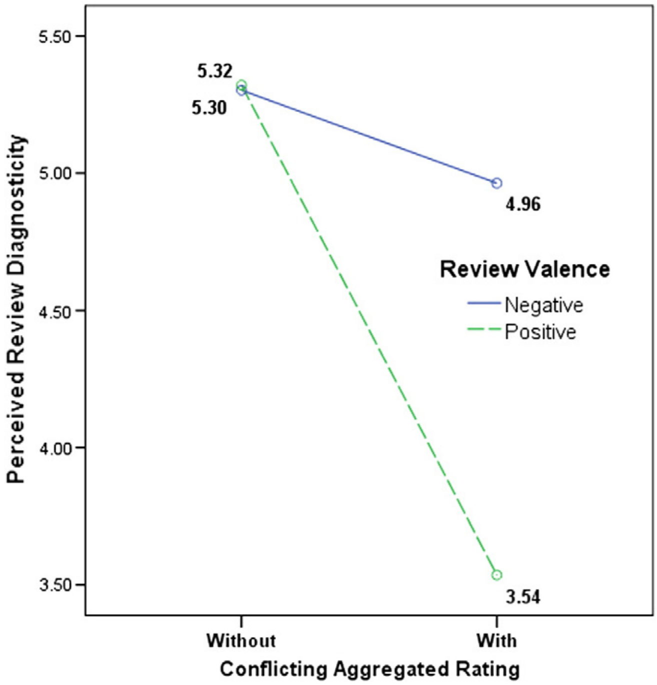

Fig. 5. Interaction between conflicting aggregated rating and review valence on review diagnosticity.

procedure suggested by Barron and Kenny [4], the Sobel test enables researchers to directly test the statistical significance of the indirect effect, that is, the difference between the total effect and the direct effect (i.e., after controlling for the effect of the mediator) of the independent variable on the dependent variable. We found that the indirect effects on both review credibility ($Z_{sobel} = -4.185$, $p<.001$) and review diagnosticity ($Z_{sobel} = -4.261$, $p<.001$) are significant, which provides additional evidence for the mediating role of review attribution.

5. Discussion

5.1. Summary of findings

As eWOM communications become an important source of product information [9,13], most B2C websites provide consumers with multiple types of eWOM information, including aggregated ratings and individual reviews. In the literature, considerable research has been conducted to demonstrate the discrete impacts of aggregated rating and individual review on consumers' product attitudes and purchasing intentions [11,49,50,58]. However, little has been known about their interactions and inconsistent views exist on whether or not the presence of an aggregated rating would influence consumers' eWOM review adoption. To fill this gap, this research investigates the effects of presenting a conflicting aggregated rating on perceived credibility and diagnosticity of the individual review, the two most important antecedents of review adoption.

The results of our laboratory experiment demonstrate that the presence of a conflicting aggregated rating has a negative effect on consumers' product-related attributions of the individual review and this effect is more salient for positive reviews than for negative ones. In addition, consumers' product-related attributions positively influence review credibility and diagnosticity. In consequence, the presence of a conflicting aggregated rating decreases perceived credibility and diagnosticity of the review via the mediating effect of review attribution. These findings are generalizable for both moderate and extreme individual reviews.

Table 5
Results of the mediation tests.

Dependent variable	R^2	Independent variable	Standardized β	*p*-Value
Review attribution	.104	Conflicting aggregated rating	−.331	<.001
Review credibility	.163	Conflicting aggregated rating	−.410	<.001
Review credibility	.496	Review attribution	.707	<.001
Review credibility	.528	Conflicting aggregated rating	−.198	.001
		Review attribution	.641	<.001
Review diagnosticity	.159	Conflicting aggregated rating	−.405	<.001
Review diagnosticity	.562	Review attribution	.752	<.001
Review diagnosticity	.587	Conflicting aggregated rating	−.176	.001
		Review attribution	.693	<.001

5.2. Theoretical contributions

The present research makes several theoretical contributions. First, to the best of our knowledge, this research is the first to focus on the conflict between aggregated rating and individual reviews and to investigate its consequences on consumers' perceptions of eWOM reviews. We find that the effects of a conflicting aggregated rating on review credibility and diagnosticity are contingent upon the valence of the review. These findings resolve the existing controversies over whether or not base rate information can influence consumer judgment in the eWOM context. Furthermore, by proposing an attributional explanation for the underlying mechanisms, this research contributes to a more in-depth understanding of consumers' responses to eWOM recommendations and provides new evidence for the importance of the attribution approach for explaining consumer behavior in eWOM communications.

Second, given that an aggregated rating is derived from a large and representative sample while individual reviews are posted by individual customers, a rational consumer should rely on the aggregated rating instead of anecdotal comments [30]. However, our findings suggest that consumers are not always as “rational” as expected. In fact, when consumers are reading a negative review, they tend to ignore the aggregated rating even though the review is conflicting with the predominant opinions. These findings are in line with the “base rate fallacy” demonstrated in early research on social cognition, which suggests that when both base-rate and individuating information is available, people often fail to make normatively appropriate use of base-rate information (e.g., population base rates, consensus information, and mean evaluations based on the ratings of all subjects) in making judgments [6,15,30,46].

A number of explanations have been proposed to account for the “base rate fallacy”. For example, Borgida and Nisbett [6,47] argue that base rate information is underutilized because it is by nature more abstract and pallid. In contrast, individuating information is vivid and concrete. Therefore, it is more cognitively available in memory [64] and is hence more likely to be utilized for judgments than base rate information [19]. A more compelling explanation is based on the notion of information relevance [5]. According to Bar-Hillel [2], people order information by its degree of perceived relevance to the problem being considered. Furthermore, information relevance is determined by its specificity, which can be achieved by providing information on a smaller set of which the target is a member rather than on the overall population, or by providing information that is related to the judgment via causality. From this point of view, people ignore base rate information in favor of individuating information, because the latter is perceived as more specific and hence more relevant [1,3,47,66]. In this research, we show that consumer attribution plays an essential role in determining the effect of a conflicting aggregated rating on consumers' perceptions of the review. These findings provide additional evidence for the relevance explanation because consumers will perceive an individual review as more relevant to product evaluation if the review is attributed to more product-related (vs. non-product-related) causes.

For positive reviews, however, we find that the presence of a conflicting aggregated rating negatively influences review credibility and diagnosticity, which seems to be incompatible with the base rate fallacy. This inconsistency may result from the anonymous nature of eWOM, which leads consumers to be more suspicious about the authenticity of online reviews than that of traditional WOM communications. As a result, they are more likely to behave in a risk-averse manner and tend to make self-serving attributions for the review when it is conflicting with the aggregated rating. Thus, our findings not only illustrate the “base rate fallacy” in the context of eWOM communications but also identify its boundary conditions as well.

5.3. Practical implications

The present research also has important implications for e-commerce practice. First, our findings suggest that the presence of a conflicting aggregated rating can prevent consumers from being overly-reliant on anecdotal reviews, in particular positive ones, which would help consumers reach more accurate product judgments and make more informed purchasing decisions. Accordingly, a well-designed B2C or eWOM website should intentionally enhance the visibility of the aggregated rating. For example, when designing their eWOM modules, most B2C websites place the aggregated rating at the top of a webpage (as illustrated in Fig. 1). Thus, this information is very likely to get out of consumers' field of vision when they scroll down the webpage. A possible solution is to use a floating panel or place the aggregated rating on both vertical ends of the webpage so that consumers are always aware of this information and are thus less likely to make biased judgments. This implication is becoming more important as most eWOM systems nowadays allow consumers to sort and filter reviews by their valence because such design makes it possible for consumers to encounter continuously positive or negative reviews without being aware that these reviews only represent a minority opinion among all the reviews. To prevent consumers from forming a biased product evaluation, it is imperative for the website to make the information of aggregated rating highly visible.

Second, our findings indicate that presenting a conflicting aggregated rating has little impact on consumers' perceptions of negative eWOM reviews. These findings imply that even though a product receives a favorable overall evaluation at the aggregate level, consumers may still largely rely on a few negative reviews in making judgments. Given the disproportional power of negative versus positive reviews, manufacturers and retailers should never underestimate the unfavorable consequences of negative reviews, not even for their most popular products. On the other hand, website designers might consider developing some new strategies to help consumers make better use of the aggregated rating rather than focusing on the minority's negative comments. For example, the website could display the distribution of individual ratings in a graphic format to increase consumers' awareness that those negative reviews only represent the opinion of a minority portion of all the reviewers.

5.4. Limitations and future research directions

While the results of our lab experiment provide supportive evidence for our hypotheses, we recognize that the present research has several limitations. First, our findings may be artificially constrained by the selection of product and the product attributes being described in the review texts. In this research, we used multimedia speakers as the target product because it is a typical experience product and most participants have experiences with this product. In addition, when preparing the review texts, we selected highly important product attributes in order to ensure the reviews' relevance and meaningfulness. Nevertheless, it would be worthwhile to replicate this study using different product categories or product attributes to enhance the generalizability of our findings.

Second, in the experiment we selected a relative large number (96) as the total number of reviews to ensure that the aggregate rating would be perceived as adequately representative. It is very likely that the impact of aggregated rating would be influenced by its perceived representativeness as well. Therefore, it is worthwhile for following studies to investigate the possible moderating role of the total number of reviews.

Finally, in the experiment, we only made one review visible to the participants to minimize the potential influences of other reviews on consumers' perceptions of the target review, which may confound the effect of aggregate rating. In real life, however, consumers can browse multiple reviews of congruent or opposite valence at the same time. Therefore, although the internal validity of this research is ensured by our well-controlled experiment, some of its external validity may have been sacrificed. Future research can investigate the effects of aggregated rating when consumers are exposed to multiple reviews.[4]

6. Conclusion

Anchored in the attribution theory, this research investigates the effects of conflicting aggregated rating on perceived credibility and diagnosticity of individual eWOM reviews. Our findings show that the presence of a conflicting aggregated rating decreases consumers' product-related attributions of the review, which in turn, negatively influences consumers' perceptions of review credibility and diagnosticity. In addition, the impacts of a conflicting aggregated rating on consumer attribution and review perceptions are more salient for positive reviews than for negative ones. These findings not only reconcile the theoretical controversies on whether or not a conflicting aggregated rating will influence consumers' eWOM review adoption and provide an attributional explanation for the underlying mechanisms, but also provide practitioners with actionable suggestions on how to improve the design of their eWOM systems.

This research constitutes an initial attempt to examine the interactions between different types of eWOM information, which is an important but underexplored topic in eWOM research. Future research can extend our findings by investigating the consequences of other instances of information interactions in an eWOM system, such as the presentation order and the display format of various eWOM system elements. In conclusion, more studies on eWOM systems can not only help academic researchers extend their understanding of how consumers process various types of eWOM information but can also benefit online retailers and third-party infomediaries by helping them improve their eWOM systems to better support online shoppers' purchasing decisions.

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[4] We thank one anonymous referee for pointing out this issue.

Appendix A. Screenshots of selected experimental webpage

Fig. A1. Webpage screenshot of group 1 (without conflicting aggregated rating + 4-star positive individual review).

Fig. A2. Webpage screenshot of group 3 (without conflicting aggregated rating + 2-star negative individual review).

Fig. A3. Webpage screenshot of group 5 (with conflicting aggregated rating + 4-star positive individual review).

Fig. A4. Webpage screenshot of group 7 (with conflicting aggregated rating + 2-star negative individual review).

Appendix B. Measurement scales and factor loadings

Construct	Cronbach's alpha	Items	Factor loadings
Product-related attribution	.805	1. To what extent does the consumer review reflect the characteristics of the product? (not at all…very much)	.694
		2. To what extent are the contents of the consumer review based on the product? (not at all…very much)	.806
Perceived review credibility	.952	1. In general, I think the consumer review I just read is _____ very untrustworthy … very trustworthy	.887
		2. In general, I think the consumer review I just read is _____ very unreliable … very reliable	.919
		3. In general, I think the consumer review I just read is _____ very incredible … very credible	.903
Perceived review diagnosticity	.886	1. Overall, how much is the consumer review useful for your product judgment? (not useful at all…very useful)	.901
		2. Overall, to what degree is the consumer's review helpful for your product judgment? (not helpful at all…very helpful)	.885
General attitude toward online reviews	.744	1. When I buy a product, online consumer reviews are helpful for my decision making.	.787
		2. When I buy a product, online consumer reviews make me confident in purchasing the product.	.780
		3. If I do not read online consumer reviews prior to purchase, I will feel worried about my decision.	.652
Subjective product knowledge	.899	1. I know pretty much about multimedia speakers.	.865
		2. I do not feel very knowledgeable about multimedia speakers. (*reverse*)	.861
		3. Among my circle of friends, I'm one of the "experts" on multimedia speakers.	.782
		4. Compared to most other people, I know less about multimedia speakers. (*reverse*)	.757
		5. When it comes to multimedia speakers, I really don't know a lot. (*reverse*)	.869

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