Why Is the Crowd Divided? Attribution for Dispersion in Online Word of Mouth

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The widespread availability of online word of mouth (WOM) enables modern consumers to assess not only the opinions of others about products and services, but also the extent to which those opinions are consistent or dispersive. Despite longstanding calls for greater understanding of mixed opinions, existing evidence is inconclusive regarding effects of WOM dispersion, and theoretical accounts have relied primarily on the notion of reference dependence. Extending prior work, this research proposes an attribution-based account, in which consumer interpretation of WOM dispersion depends on the extent to which tastes in a product domain are perceived to be dissimilar, so that dispersion can be attributed to inconsistency in reviewer preferences rather than the product itself. Across four experimental studies, participants presented with online rating distributions were more tolerant of dispersion in taste-dissimilar product domains than taste-similar product domains, and the difference was driven by underlying attributions. Together, these findings expand current understanding of WOM, social distributions, and risk perception, by revealing distinct pathways through which consumers respond to differences of opinion. In addition, they suggest the opportunity to proactively influence the manner in which dispersion is perceived, highlighting its positive connotations while diminishing its association with risk.

Empowered by information technology, modern consumers have available a vast array of word of mouth (WOM) to inform their purchase decisions. As a consequence, they are more likely than ever to encounter a mixture of positive and negative opinions about the same product or service. Surveys of online rating platforms show that mixed opinions are common: dispersion in consumer ratings tends to vary widely across products, both within and across categories, and is often bimodal (Hu, Pavlou, and Zhang 2009; Moe and Schweidel 2012). Our research addresses the influence of such dispersion on consumer decision making. Are consumers influenced by dispersion in the WOM that they encounter, and, if so, does it have a systematic effect on judgment or choice?

In contrast to a large body of recent WOM research examining individual product ratings, ratings volume, and central tendency (Chen and Lurie 2013; Chevalier and Mayzlin 2006; Mudambi and Schuff 2010), little work has focused directly on dispersion. Moreover, a small collection of studies incorporating dispersion have revealed positive, negative, and inconclusive effects (Moe and Trusov 2011; Moon, Bergey, and Iacobucci 2010; Zhu and Zhang 2010). These conflicting findings suggest the presence of important moderators worthy of investigation.

Dispersion in WOM provides a measure of evaluative consensus. By exploring its influence on perceivers, we respond to a longstanding call for more thorough study into the role of consensus in social information (West and Broniarczyk 1998). We begin by constructing a framework based on relevant theories in social perception and attribution. Our framework proposes that consumers who encounter dispersion in WOM naturally seek to explain that dispersion and do so by attributing it to one of two causes: the product itself or characteristics of the reviewers. In line with prior research, we argue that dispersion attributed to variability

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in the product experience will generally be considered undesirable (Matz and Wood 2005; Urbany, Dickson, and Wilkie 1989). In contrast, however, dispersion attributed to variability in reviewer characteristics will tend to be viewed more favorably. To predict the direction of attribution, we focus on the role of perceived taste similarity—that is, the extent to which tastes in a product domain are expected to differ. By doing so, we extend prior work on consumer attribution by proposing taste similarity as an important moderator of attributional inference.

In the following sections, we develop a conceptual framework based on relevant research in social cognition, attribution, and consumer WOM. We then present a series of laboratory studies testing our framework across distinct judgment and decision settings. We conclude by discussing implications for marketers, retailers, and consumers.

CONCEPTUAL BACKGROUND

Aggregated Word of Mouth as a Social Distribution

Social psychologists have long been interested in individual beliefs regarding the ways that attitudes and behaviors vary in group settings. Within this field, one stream of research has focused on the formation and accuracy of beliefs about social distributions (Gershoff and Burson 2011; Nisbett and Kunda 1985; Peterson and Beach 1967), and a separate stream has focused on the role of social distributions in individual judgment and decision making (Epley and Dunning 2000; Goel, Mason, and Watts 2010; Linville, Fischer, and Salovey 1989; Van Boven, Judd, and Sherman 2012). Findings in the latter stream indicate that information about social distributions can exert powerful social influence, affecting decisions across a range of domains.

In the past, consumers were rarely exposed to information regarding the distribution of evaluations for goods and services in the marketplace. Individual consumers observed only a small sample of others' evaluations, primarily through traditional communication channels. As such, the consumer WOM literature tended to focus on the influence of specific individuals or small groups—such as friends, family members, and critics (Arndt 1967; Brown and Reingen 1987). However, the emergence of e-commerce and online communications has provided access to a much larger sample, so that consumers have at their disposal the opinions of thousands of strangers (restaurant reviews at Yelp, movie ratings at IMDb, forum posts at CNET, etc.). Given the sheer number of opinions available, it is common for online platforms to summarize evaluations in graphical form, making their distribution apparent (see figs. 1 and 2 for examples). As a result, their distribution may play an increasingly important role in consumer decision making.

Only recently have researchers begun to focus on the processes by which consumers incorporate the WOM of numerous, anonymous sources. As with any distribution, the WOM distribution for a specific product can be described by characteristics such as volume, central tendency, dispersion, skew, and so forth. Of these characteristics, volume and central tendency have received the vast majority of attention (see table 1). A wide range of empirical studies, using diverse product categories, has demonstrated a direct and positive effect of WOM volume on sales and related variables (Chevalier and Mayzlin 2006; Dellarocas et al. 2007; Duan, Gu, and Whinston 2008; Li and Hitt 2008; Liu 2006; Moe and Trusov 2011; Sun 2012; Zhu and Zhang 2010). Similarly, higher average product ratings have been consistently associated with increased purchase likelihood (Chevalier and Mayzlin 2006; Chintagunta, Gopinath, and Venkataraman 2010; Clemons, Gao, and Hitt 2006; Dellarocas, Zhang, and Awad 2007; Li and Hitt 2008; Moe and Trusov 2011; Moon et al. 2010; Sun 2012; Zhu and Zhang 2010).

Mixed Findings on Mixed Opinions

In contrast to volume or central tendency, the influence of WOM dispersion on consumer perceptions remains poorly understood. Adopting the approach of others (Clemons et al. 2006), we operationalize WOM dispersion in terms of statistical variance—that is, the second moment of product ratings. Within a small stream of empirical research, findings on the downstream impact of dispersion are mixed. On the one hand, higher dispersion has been associated with lower sales in some categories (Zhu and Zhang 2010) but higher sales in other categories (Clemons, Gao, and Hitt 2006; Moe and Trusov 2011). An illustrative example is the movie category, for which Moon et al. (2010) found higher dispersion to be associated with lower satisfaction, Chintagunta et al. (2010) found no effects on revenue, and Martin, Barron, and Norton (2008) found positive effects on choice. In most of these examples, dispersion was not the primary focus, and no attempt was made to reconcile the seemingly conflicted findings; however, their presence suggests the influence of important moderating variables.

A small body of research has specifically addressed the interaction of WOM dispersion with other distributional characteristics (Khare, Labrecque, and Asare 2011; Meyer 1981; Sun 2012; West and Broniarczyk 1998). Most of this work is predicated on tenets of prospect theory (Kahneman and Tversky 1979), under the assumption that consumers interpret a distribution of others' evaluations to represent the possible outcomes that they might themselves experience. Existing research focuses on the principle of reference dependence, by which decision makers tend to be risk-seeking when choosing among losses and risk-averse when choosing among gains (Heath, Chatterjee, and France 1995; Thaler 1985; Tversky and Kahneman 1991). Prominent examples include experimental studies conducted by Meyer (1981) and West and Broniarczyk (1998), in which participants responded to decision scenarios that included the opinions of multiple critics; across different conditions, the average opinion and consensus of critics was varied. Consistent with loss aversion, participants preferred options with critical consensus when average opinions were favorable (above aspiration levels), but preference for consensus was reduced or reversed when average

FIGURE 1

WORD OF MOUTH (HIGH DISPERSION)

NOTE.—Retrieved July 7, 2011, from http://www.amazon.com/Magic-Bullet-Express-17-Piece-High-Speed/dp/B000AEZVRS.

opinions were unfavorable (below aspiration levels). More recent work applies the reference-dependent approach to distributions of online WOM in the form of consumer ratings. Adopting a game-theoretic framework, Sun (2012) finds that the association between ratings variance and sales in the online books category is negative at high average ratings but positive at lower average ratings. In an experimental setting, Khare et al. (2011) reveal a similar interaction between dispersion and average ratings but only when WOM volume is large (e.g., thousands of ratings). Martin et al (2008) document preference for greater dispersion in domains characterized by high aspiration levels (e.g., movies, desserts) but preference for lower dispersion in domains characterized by low aspiration levels (e.g., dental procedures, “disgusting” foods).

Approaches based on reference-dependence have provided important insights regarding the interpretation of WOM dispersion by prospective consumers. However, they cannot fully account for the contradictory empirical findings above, in which the effects of dispersion have been shown to vary across product categories (and in some cases, within categories) in a manner that is difficult to explain through aspiration levels. Although these findings suggest that the interpretation of dispersion varies across categories, no existing work has identified the source of these differences. More generally, prior approaches have focused on only one aspect of the underlying cognitive process, and further research is needed to better understand the multifaceted influence of WOM dispersion on consumer judgment. In the following sections, we supplement existing approaches with an attributional framework, in which the effect of WOM dispersion depends on inferences regarding its underlying cause.

Attributions for Dispersion and the Role of Taste Similarity

Rather than passively observing events as they unfold, individuals often make inferences about the causes underlying those events (Heider 1958; Jones and Davis 1965). Although explanatory thinking is a fundamental (and often automatic) psychological process, certain characteristics

FIGURE 2

WORD OF MOUTH (LOW DISPERSION)

NOTE.—Retrieved December 13, 2013, from http://www.yelp.com/biz/rosas-pizza-and-pasta-new-york-2.

make an event more or less likely to evoke attributions. For example, attributional inference making is enhanced for observations that are unexpected, relevant to active goals, or affectively impactive (Hastie 1984; Kelley 1973; Weiner 1972). An especially relevant line of research examines the (often biased) process by which individuals assign causal agency to outcomes experienced by others (Burger 1981; Gilbert and Malone 1995; Rim, Hansen, and Trope 2013). Importantly, this process can be triggered by observed attitudes as well as observed behaviors, and targets can be individuals or groups (Kenworthy and Miller 2002; O'Laughlin and Malle 2002). Therefore, our model begins with the assertion that consumers aware of WOM dispersion will often engage in attributional processing to explain it.

To what causal agents may dispersion in product WOM be attributed? In principle, variance in reported product satisfaction may be caused by a vast array of factors: for instance, different visitors to an art museum may report different satisfaction based on the time of year, the traffic, or the exhibits that they encounter. However, a wide range of potential attributions can be categorized into either: (1) sources related to the product or (2) sources related to the reviewers. This distinction between product and reviewer attributions is consistent with work cited earlier and with recent research in online WOM; for example, Chen and Lurie (2013) demonstrate how the valence of a product review affects attribution to product or reviewer characteristics. On the one hand, consumers often view product-related WOM as an indication of the degree to which a product performs according to what is promised or expected. For example, a lamp may stop working in a week or may last for years; a restaurant may or may not have its celebrity chef in the kitchen on a given day. Past work on dispersion has implicitly focused on such product-related attributions (Khare et al. 2011; Sun 2012; West and Broniarczyk 1998). However, the presentation of WOM in distributional form highlights a possible alternative cause—variability in the reviewers who contributed to that distribution. Different people may evaluate the same features differently, weigh their relative importance differently or utilize different standards for evaluation, and consumers who encounter dispersion may consider these differences when forming their impressions. This notion is consistent with evidence that observers often attribute product performance to aspects of users (Folkes 1988), that negative WOM in particular is frequently attributed to incorrect product usage (Laczniak, DeCarlo, and Ramaswami 2001). Therefore, we argue that dispersion in WOM will often be viewed as a consequence of variance in reviewer characteristics.

When will the attribution process result in an inference of product causality versus reviewer causality? A fundamental principle of attribution theory (Kelley 1973) is that when explaining the behavior of an actor, observers take into account how others behave in the same situation (i.e., consensus information). When most others behave similarly to the actor, observers are likely to infer causes external to the actor, but as consensus decreases, attributions become more internal (McGill 1989; Orvis, Cunningham, and Kelley 1975). This principle extends readily to our setting, in which the dispersion of a WOM distribution provides prospective consumers with information about the consensus of prior consumer evaluations. At one extreme is a very narrow

TABLE 1

EMPIRICAL LITERATURE ON CONSEQUENCES OF WOM DISTRIBUTION CHARACTERISTICS

			Characteristic of the distribution		
Article	Product domain	Dependent variable	Volume	Average	Dispersion
Godes and Mayzlin (2004)	TV shows	TV ratings	No effect		
Chevalier and Mayzlin (2006)	Books	Book sales rank	Positive effect	Positive effect	
Clemons et al. (2006)	Crafted beer	Sales growth rate	No effect	Positive effect	Positive effect
Liu (2006)	Movies	Box office revenue	Positive effect	No effect	
Dellarocas et al. (2007)	Movies	Box office revenue	Positive effect	Positive effect	
Duan et al. (2008)	Movies	Box office revenue	Positive effect	No effect	
Li and Hitt (2008)	Books	Book sales rank	Positive effect	Positive effect	
Chintagunta et al. (2010)	Movies	Box office revenue	No effect	Positive effect	No effect
Moon et al. (2010)	Movies	Box office revenue, satisfaction	Negative effect on satisfaction	Positive effect with ad spending (interaction)	Negative effect on satisfaction
Zhu and Zhang (2010)	Video games	Game sales	Positive effect	Positive effect	Negative effect
Sun (2012)	Books	Book sales rank	Positive effect	Positive effect	Negative effect with high average (interaction)
Moe and Trusov (2011)	Bath, fragrance, and beauty products	Cross-product sales and ratings	Positive effect on sales, negative effect on ratings	Positive effect on sales, negative effect on ratings	Positive effect on sales, negative effect on extreme ratings
Sridhar and Srinivasan (2012)	Hotels	Hotel rating	No effect	Positive effect and interactions with product features	

distribution, in which nearly all reviewers have assigned the same evaluation (i.e., consensus is high). For prospective consumers encountering such a distribution, the presence of high consensus will be conducive to a product (vs. reviewer) attribution. However, as the dispersion of the distribution increases (indicating lower and lower consensus), observers will be increasingly likely to attribute that dispersion to reviewer characteristics.

The process described thus far is consistent with prior work on the role of consensus in attribution. However, the consumer WOM setting involves unique characteristics that allow for a more nuanced prediction. In this setting, we propose that a key influence on attributions is the extent to which reviewer tastes are expected to vary. This idea builds on prior research showing that consumer responses to WOM often depend heavily on the degree to which preferences in the population are homogeneous or heterogeneous (Naylor, Lamberton, and Norton 2011; Price, Feick, and Higie 1989). In general, products can be categorized by the extent to which consumers share similar preferences, and consumers possess lay theories about taste similarity for different product domains (Berger and Heath 2007; Gershoff and West 1998; Price et al. 1989). For domains where tastes are assumed to be highly similar (e.g., a flash drive), consumers should expect that reviewers having a very similar experience with the product will assign equivalent evaluations; therefore, WOM dispersion will more readily be attributed to the product than to the reviewers. For example, after observing that a flash drive has received a wide range of evaluations, consumers are more likely to attribute that dispersion to inconsistent product quality or performance than to variance in user preferences or expectations. However, for domains where tastes are known to be dissimilar, WOM dispersion is more easily attributed to reviewer causes. For example, given that preferences in music and art are subjective and vary markedly, consumers encountering disperse WOM may simply assume that different reviewers had differing expectations for their experiences. In contrast to traditional models, therefore, we propose that the low consensus indicated by disperse WOM may or may not evoke greater reviewer attribution, depending on assumptions regarding taste similarity.

Consequences of Attribution

Our final proposition is that attributions for dispersion will affect product-related judgment and choice. When WOM is attributed to the product, its valence indicates the degree to which the product performs as promised (Khare et al. 2011; Sun 2012; West and Broniarczyk 1998), and its dispersion indicates variability in that performance (e.g., quality control problems, variance in individual attributes, inconsistency across time or usage occasion). As a result, higher dispersion should increase perceived outcome uncertainty and risk, affecting judgments negatively. In contrast, the implications of WOM attributed to reviewer characteristics are markedly less negative. In fact, reviewer-attributed dispersion presents consumers with opportunities to learn about their own preferences (i.e., extensive learning; Hoeffler et al. 2013), to satisfy curiosity about their potential experience (Raju 1980), or to demonstrate open-mindedness (Ratner and Kahn 2002). Together, these opportunities should mitigate the negative effects of dispersion on product evaluations.

Our conceptual framework is summarized in figure 3. Formally, we predict the following:

H1: The negative influence of WOM dispersion on product evaluations is stronger for taste-similar domains than for taste-dissimilar domains.

H2: The moderating influence of taste similarity on product evaluations is mediated by attributions for WOM dispersion.

OVERVIEW OF STUDIES

Across four studies, we presented participants with product decision scenarios that included information about the evaluations of prior consumers, in the form of both an overall average rating and an illustration of the underlying rating distribution. To distinguish from prior research focused on reference-dependence, studies 1, 3, and 4 utilized WOM distributions for which the average rating was above aspiration levels. In study 2, average rating was manipulated directly to examine the robustness of our predictions. Similar to most prior research on WOM dispersion (Meyer 1981; West and Broniarczyk 1998), studies 1–2 utilized within-subject designs; however, the final two studies address this limitation with between-subjects designs.

STUDY 1: THE INFLUENCE OF WOM DISPERSION AND PRODUCT DOMAIN ON CHOICE

Our first study examined the combined effects of WOM dispersion and taste similarity in a choice setting. Participants were asked to choose between products characterized by various rating distributions, presented in graphical form, from a variety of product domains. Given that average ratings are positive for the vast majority of products at real-world platforms (Chevalier and Mayzlin 2006; Li and Hitt 2008) and consumers will tend to avoid low-rated options, the stimuli for the study consisted of products with average ratings well above the midpoint. Thus, prospect theory and the broader principle of risk aversion suggest that individuals will prefer consensus over dispersion. Over and above this tendency, however, our model predicts that individuals will be more likely to choose a high-dispersion option over a low-dispersion option for domains characterized by dissimilar tastes.

Choice pairs in the stimuli presented three different types of trade-off between average rating and dispersion (described below). These different trade-offs helped to disguise our dispersion manipulation, by ensuring that distributions in the pairs were not distinguished by variance alone and also allowed us to explore questions related to the robustness of our framework.

Method

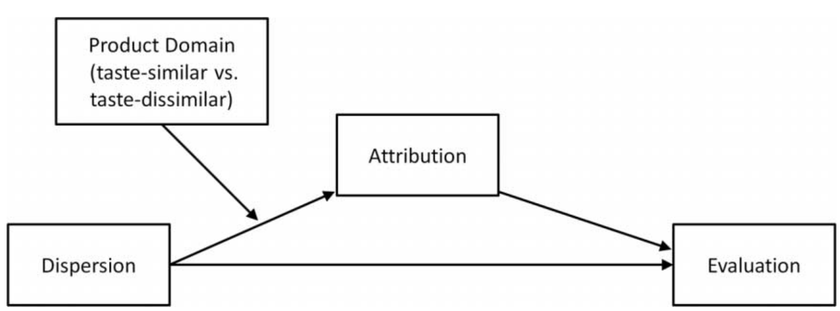
Pretest. In a pretest, 27 undergraduate students at the Georgia Institute of Technology were presented with a list of product domains and asked to rate the taste similarity of each domain, using a 100 point scale (1 = "not at all similar," 100 = "very similar"). Based on the results, four product domains (two taste-similar, two taste-dissimilar) were chosen for use in the study. The two taste-similar domains included desk lamps and flash drives ($M = 66.85$ and 66.24). The two taste-dissimilar domains included framed paintings and music albums ($M = 42.00$ and 37.17). Analysis confirmed that taste similarity ratings differed across the two sets of domains (66.55 vs. 39.58; $t(26) = 5.72$, $p < .001$).

In a separate pretest of aspiration levels, 104 undergraduate students were asked to state the minimum average rating (1–10) required for products in their consideration set. Results indicated that the average aspiration level was 5.07 (SD = 1.06). As described below, stimuli in the main study were constructed with average ratings above this level.

Main Study. The design of study 1 included two within-

FIGURE 3

CONCEPTUAL MODEL



subject factors: product domain (taste-similar, taste-dissimilar) and trade-off type (three levels, described below). The study was conducted in a university laboratory, and 113 undergraduates (mean age = 25, 48% female) participated in exchange for course credit. In the cover story, participants were told they would be making hypothetical choices across a range of different products, based on the information provided.

On subsequent screens, participants were presented with eight different choice pairs, each representing a different product domain. For each option in a choice pair, the screen displayed information about the average and distribution of prior consumer ratings. The information display format, illustrated in figure 4, was consistent with that used at prominent online platforms. In all cases, the distribution contained ratings from 40 reviewers. Ratings were presented on a scale of 1–10 "stars," with more stars reflecting greater satisfaction; next to each star rating, the number of reviewers who assigned that rating was indicated with a horizontal bar. At the top of each distribution, the overall average rating was provided. After examining the information, participants were asked to select one of the two options.

The three choice trade-off types were designed as follows. In the *disperse-higher* trade-offs, participants compared an option with an average rating of 7.5 stars and high dispersion to an option with an average rating of 6.5 stars and low dispersion. In the *disperse-lower* trade-offs, the option with a higher average rating (7.5 stars vs. 6.5 stars) also had lower dispersion. Finally, in the *equal-rating* trade-offs, both options had an average rating of 7 stars, but dispersion was high for one option and low for the other. Stimuli were presented according to a Greco-Latin square design, in which each participant was shown all three trade-off types for all four product domains. Finally, four filler choice pairs

TABLE 2

STUDY 1: RELATIVE CHOICE SHARES OF THE HIGH-DISPERSION OPTION AS A FUNCTION OF PRODUCT DOMAIN AND TRADE-OFF TYPE

	Trade-off type		
	Disperse-high	Equal-rating	Disperse-low
Taste-similar categories:			
Desk lamp	69.2 (N = 39)	34.1 (N = 41)	6.1 (N = 33)
Flash drive	51.5 (N = 33)	35.9 (N = 39)	7.3 (N = 41)
Combined	61.1 (N = 72)	35.0 (N = 80)	6.8 (N = 74)
Taste-dissimilar categories:			
Painting	76.9 (N = 39)	56.1 (N = 41)	21.2 (N = 33)
Music album	63.6 (N = 33)	48.7 (N = 39)	43.9 (N = 41)
Combined	70.8 (N = 72)	52.5 (N = 80)	33.8 (N = 74)

NOTE.—Values represent percentage of participants choosing the high dispersion option. In disperse-high (disperse-low) trade-offs, the average rating was higher (lower) for the high-dispersion option than the low-dispersion option.

(movies, audio speakers, car mechanics, and night clubs) were added to avoid repetition and disguise the dispersion manipulation. The eight product domains were presented in one of two random orderings, and the left-right positions of options were counterbalanced across choice pairs.

Results

Our framework predicts that consumers will be more likely to tolerate options with high dispersion in contexts where tastes are expected to be dissimilar. Table 2 presents the relative choice shares of the high-dispersion option in

FIGURE 4

STUDY 1: STIMULUS DISTRIBUTION EXAMPLE

each condition. Initial analyses revealed a pattern consistent with predictions: averaging across all three trade-off types, the high-dispersion option was chosen by only 34.1% of participants in taste-similar domains (desk lamps and flash drives), but by 52.2% of participants in taste-dissimilar domains (paintings and music albums). Chi-squared comparisons revealed that the increase in choice of high-dispersion options for taste-dissimilar domains was significant for two out of the three trade-off types: *equal-rating* (35.0% vs. 52.5%, $\chi^2(1) = 4.98$, $p < .05$), and *disperse-lower* (6.8% vs. 33.8%, $\chi^2(1) = 16.72$, $p < .001$). For the *disperse-higher* trade-off type, the increase was only directional (61.1% vs. 70.8%, $\chi^2(1) = 1.52$, NS).

As a formal test of our hypothesis, we performed a repeated-measure logistic regression in which choice of the high-dispersion option was predicted by product domain, trade-off type, and their interaction. Unsurprisingly, analyses revealed a main effect of trade-off type ($\chi^2(2) = 49.19$, $p < .001$): participants overwhelmingly rejected options with greater dispersion and a lower average rating (*disperse-lower*: 20.3%), but they were more willing to accept options with greater dispersion and a higher rating (*disperse-higher*: 66.0%). Most importantly, analyses also revealed a significant main effect of product domain ($\chi^2(1) = 20.07$, $p < .001$). Consistent with predictions, participants were more likely to choose high-dispersion options in taste-dissimilar domains. Finally, a product domain × trade-off type interaction ($\chi^2(2) = 7.41$, $p < .05$) indicated that the effect of product domain was strongest in the *disperse-lower* conditions.

Discussion

Study 1 provided initial support for our claim that the impact of WOM dispersion on consumer choice depends on the level of taste similarity associated with product domains. When making choices based on a rating distribution of prior consumers, participants were more willing to opt for a high-dispersion option in product domains characterized by dissimilar tastes. Similar findings were obtained across multiple product domains, reducing the likelihood that domain-specific factors were responsible for the effect (we address this issue further in studies 3–4). Moreover, findings were robust to different trade-off contexts. Of particular interest were findings for *disperse-lower* trade-offs in taste-dissimilar domains, where seemingly dominated options offered both lower average rating and higher dispersion than their alternatives but were nonetheless chosen by almost 30% of participants.

STUDY 2: THE INFLUENCE OF DISPERSION AND PRODUCT DOMAIN ON ATTRIBUTIONS AND INTENTION

Study 2 extended our investigation in three important ways. First, we examined purchase intention as the primary dependent measure. If consumers are more tolerant of WOM dispersion when they perceive that tastes differ, then the negative impact of dispersion on purchase intention should lessen in product domains characterized by taste dissimilarity. Second, we utilized a range of average ratings in order to examine the robustness of our findings and address concerns that our predicted interaction may obtain only for choices between gains. Third, we directly measured the causal attributions that participants generated for the dispersion they encountered. These process measures enabled a formal test of our mediation framework.

Method

Experimental Procedure. One hundred ninety-two US residents (mean age = 32, 55% female) were recruited from the Amazon Mechanical Turk platform and compensated for their time. The cover story asked participants to imagine that they were shopping on a popular online retail site. Participants were randomly assigned to either the taste-similar domain (lamps) or the taste-dissimilar domain (paintings) and instructed that they would be making a series of independent decisions about products in the category. Both dispersion and mean rating were manipulated within-subjects, as described below.

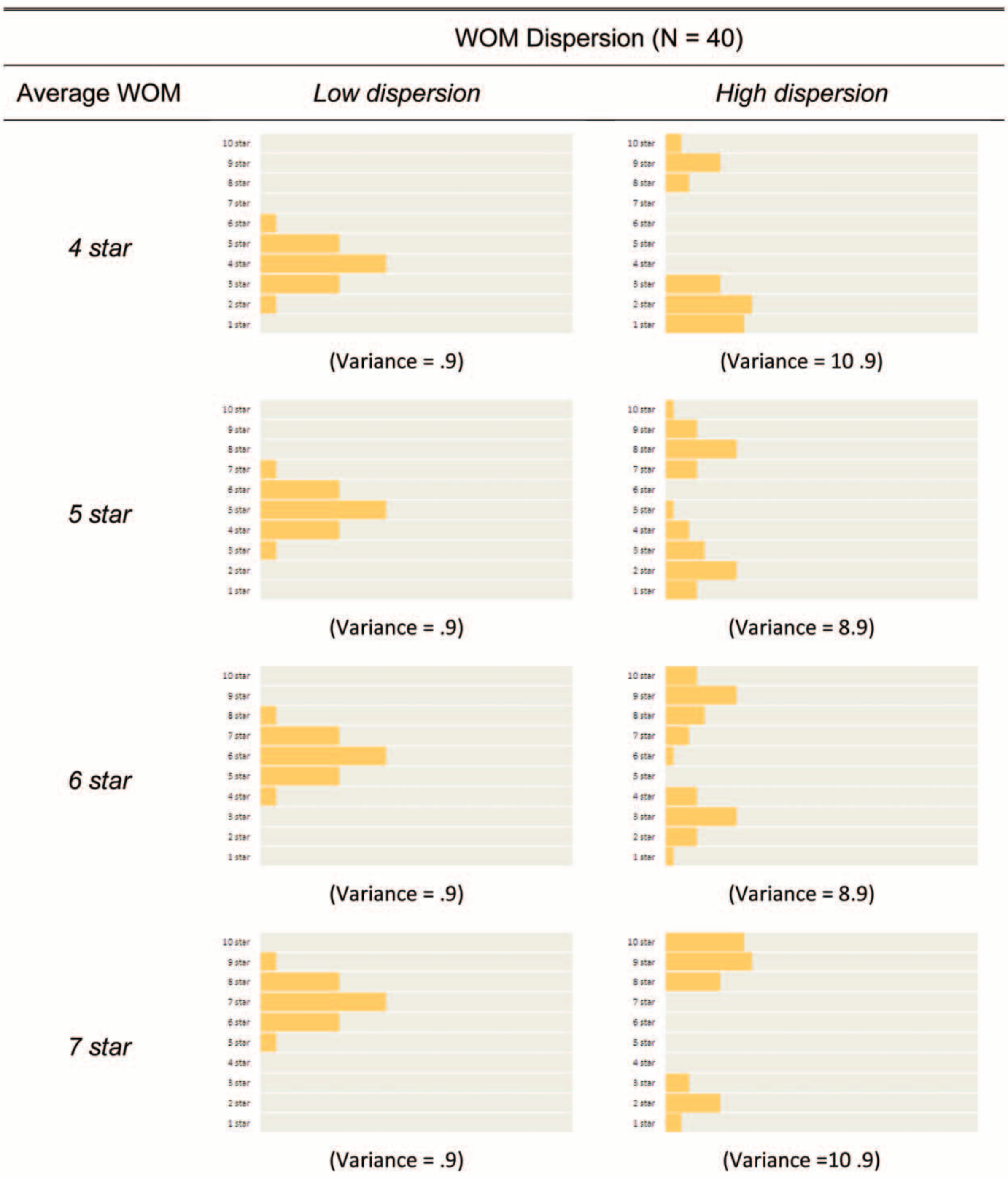
On the next screens, participants were presented with 16 different product decisions, one at a time. Each decision included a product rating distribution in the form of a bar chart, similar to study 1 and shown in figure 5. After viewing the distribution for each product, participants responded to two questions measuring purchase intentions and causal attributions (see below). Next, they completed a short demographic questionnaire. Given the inherent lack of control and observability on Mechanical Turk, we included in the demographic questionnaire a modified version of the instructional manipulation check (IMC; Oppenheimer, Meyvis, and Davidenko 2009), in which a seemingly straightforward multiple-choice item was preceded by detailed instructions asking for a specific response. Similar versions of the IMC have documented failure rates of 14% to 46% (Oppenheimer et al. 2009). After completing the questionnaire, participants were thanked and dismissed.

The 16 different distributions included eight target distributions along with eight fillers (to avoid repetition and disguise the purpose of the study). Target distributions were constructed with four different average ratings: four, five, six, and seven stars. For each rating, one target distribution depicted low variance ($var < 1.0$), and the other target distribution depicted high variance ($var > 8.00$). Fillers included a unanimous distribution in which all reviewers assigned the same rating and a flattened distribution in which similar numbers of reviewers assigned each rating possible. The set of 16 distributions was arranged into two different presentation orders, which were counterbalanced during presentation.

Purchase Intention. For each of the 16 scenarios, participants reported their purchase intention on a 7-point scale (1 = "not very likely," 7 = "very likely").

FIGURE 5

STUDY 2: DISTIRIBUTION STIMULI



NOTE.—The variances provided in the figure were not shown to participants.

Causal Attribution. To measure causal attributions, we used a bipolar scale adapted from prior attribution literature and recent WOM research (Chen and Lurie 2013). Participants responded to the question, “Do you think the product or the reviewers was more responsible for the ratings above?” using a 7-point scale (1 = “the product,” 7 = “the reviewers”). Therefore, higher (lower) scores indicated greater reviewer (product) attribution.

Results

Purchase Intention. Forty-six participants who failed the IMC were discarded prior to analysis, leaving a sample of 146 participants. Table 3 presents mean purchase intention for each level of average rating, product domain, and dispersion. Analysis of intention was conducted using a mixed ANOVA, in which product domain (taste-similar vs. taste-dissimilar) was entered as a between-subjects factor, and both average rating (four to seven stars) and dispersion (low vs. high) were entered as repeated-measure factors. Results of the ANOVA revealed a main effect of average rating ($F(3, 1008) = 297.75$, $p < .001$), such that participants preferred products with a higher rating. However, rating did not significantly interact with any other effects. Analyses also revealed a main effect of dispersion ($F(1, 1{,}008) = 11.80$, $p = .001$), such that less dispersion was preferred overall. Most important, and consistent with our predictions, this main effect was qualified by a significant interaction between product domain and dispersion ($F(1, 1{,}008) = 5.29$, $p < .05$), as depicted in figure 6. Planned follow-up contrasts revealed that in the taste-similar domain, participants assigned higher purchase intention to products with low dispersion than to products with high dispersion (3.54 vs. 3.20; $F(1, 1{,}008) = 15.58$, $p < .001$). In the taste-dissimilar domain, however, no significant difference was observed between low and high dispersion (3.68 vs. 3.61; $F < 1$, NS).

Causal Attribution. According to our framework, high levels of WOM dispersion are more likely to be attributed to reviewer causes when a product domain is characterized

TABLE 3

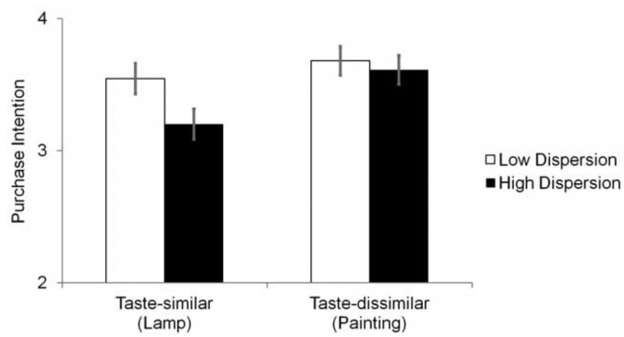
STUDY 2: PURCHASE INTENTION BY WOM DISPERSION, PRODUCT DOMAIN, AND WOM AVERAGE

		Product domain	
WOM average	WOM dispersion	Taste-similar (lamp)	Taste-dissimilar (painting)
Rating = 7	Low	4.86 (.16)	4.74 (.15)
	High	4.45 (.16)	4.69 (.15)
Rating = 6	Low	4.04 (.16)	4.21 (.15)
	High	3.42 (.16)	4.05 (.15)
Rating = 5	Low	3.14 (.16)	3.35 (.15)
	High	2.84 (.16)	3.25 (.15)
Rating = 4	Low	2.13 (.16)	2.42 (.15)
	High	2.09 (.16)	2.45 (.15)

NOTE.—Standard errors are reported in parentheses.

FIGURE 6

STUDY 2: PURCHASE INTENTION AS A FUNCTION OF PRODUCT DOMAIN AND WOM DISPERSION



by dissimilar tastes. Analysis of the causal attribution measure was conducted using a mixed ANOVA with the same three predictor variables and interactions described above. Results of the ANOVA revealed significant main effects of product domain ($F(1, 1008) = 5.39$, $p = .02$), average rating ($F(3, 1008) = 20.87$, $p < .001$), and dispersion ($F(1, 1008) = 50.10$, $p = .001$). Most important, results also revealed a significant interaction between product domain and dispersion ($F(1, 1008) = 11.24$, $p = .001$), and the pattern was consistent with predictions. For both product domains, participants assigned higher reviewer attribution when dispersion was high than when dispersion was low (taste similar: 4.00 vs. 3.68, $d = .32$, $p = .01$; taste dissimilar: 4.68 vs. 3.79, $d = .89$, $p < .001$), but the increase was larger in the taste-dissimilar domain.

As a test of our process model, we conducted a moderated mediation analysis, using bootstrapping with repeated extraction of 5,000 samples (Hayes 2013, model 7). The mediation analysis included dispersion as the independent variable (0 = low, 1 = high), product domain as the moderator (0 = taste similar, 1 = taste dissimilar), causal attribution as the mediator, and purchase intention as the dependent variable. Results indicated that the indirect pathway through attribution was positive and significant (B = .17, SE = .06), and the 95% confidence interval (CI) excluded zero (95% CI: .06, .30). Follow-up analyses of conditional indirect effects revealed that the effect of dispersion through attribution was stronger for the taste-dissimilar domain (B = .27, SE = .05, 95% CI: .18, .37) than for the taste-similar domain (B = .09, SE = .05, 95% CI: .01, .19). Moreover, after controlling for attribution, the direct effect of domain × dispersion on purchase intention was no longer significant (B = .11, SE = .18, NS).

Discussion

Extending our investigation to a judgment setting, study 2 provided additional evidence that interpretation of WOM dispersion depends on the degree of taste similarity associated with different product domains. Although participants showed a general preference for products whose ratings distributions exhibited low dispersion, they were much more tolerant of dispersion in a domain characterized by dissimilar tastes. Moreover, mediation analyses confirmed that taste similarity influenced the attributional process by which participants explained WOM dispersion.

Although not our primary focus, the pattern of results was generally consistent with the principle of reference-dependence. For example, collapsing across product categories, high dispersion was associated with lower purchase intention when average ratings were high (seven stars: $M_{\text{high}} = 4.57$ vs. $M_{\text{low}} = 4.80$; $F(1, 1008) = 3.63$, $p = .06$) but not when average ratings were low (four stars: $M_{\text{high}} = 2.27$ vs. $M_{\text{low}} = 2.27$; $F(1, 1008) < 1$, NS). Because aspiration levels were not measured directly, these results should be interpreted with caution. More importantly, our predicted pattern of results was robust across average ratings, reinforcing our argument that an attributional framework offers a valuable supplement to prior approaches.

In studies 1–2, taste similarity was manipulated by varying the product domain to which decisions pertained. Although a variety of domains were utilized, it is plausible that results were driven by other, confounding factors: for example, aspiration levels or expectations regarding variance may have varied systematically across the products included in the studies. More generally, the products may have differed in the extent to which they evoked risk aversion. We address these concerns in study 3 by incorporating a direct manipulation of taste similarity.

STUDY 3: VARYING TASTE SIMILARITY WITHIN PRODUCT

In our third study, we manipulated taste similarity directly, through information provided to participants about the reviewers underlying the WOM distributions presented. Specifically, half of participants were told that reviewers had very dissimilar tastes, while half of participants received no information about taste similarity. Based on our model and results of studies 1–2, we predicted that participants who were informed that reviewers had dissimilar tastes would be more tolerant of WOM dispersion. In addition, we examined a product domain (ice cream) characterized by diverse options and highly subjective preferences. For such domains, we speculated that dispersion attributed to reviewers may be perceived as not only tolerable but actually desirable. Therefore, we included a number of exploratory items measuring potential benefits of reviewer-attributed dispersion.

Method

Experimental Procedure. Three hundred thirty-two US residents (mean age = 34, 61% female) were recruited from the Mechanical Turk platform in exchange for payment. The stimuli and procedure were adapted from research by Gershoff, Mukherjee, and Mukhopadhyay (2007). Participants were randomly assigned to a 2 (WOM dispersion: *low* vs. *high*) × 2 (taste similarity: *control* vs. *taste dissimilar*) between-subjects design. The cover story involved a local ice cream shop that was test marketing a new variety of ice cream sundae. As part of the story, participants were given a list of different flavors and toppings and asked to create three ice-cream sundaes; the purpose of this initial task was to enhance realism and involvement in the study. Next, participants were told that they would be choosing between two new ice cream sundaes, based on the evaluations provided by 97 "prior participants in our research." In the control condtion, participants were told simply that the 97 reviewers had participated "during the last two weeks." In the taste-dissimilar condition, participants were told that the evaluations were provided by 97 reviewers during the last two weeks "whose preferences were very different from each other," based on the sundaes they had created during the initial task; specifically, these reviewers "chose very different combinations of flavors and toppings," such that no more than one flavor or topping was shared by any two reviewers in the group.

The two sundaes in the choice task were represented by WOM distributions similar to those in studies 1–2. Of the two options presented, one was the target stimulus, and the other was a clearly inferior decoy option whose role was to strengthen the manipulation of dispersion. For each sundae, participants observed both an overall average rating (1–5 stars) and a chart depicting the number of prior reviewers assigning each rating. In all conditions, the target option had received an average rating of four stars, the decoy had received an average rating of three stars, and variance in ratings for the decoy was 2.12. Ratings variance for the target option differed by condition: in the low-dispersion condition, variance was 0.25, and in the high-dispersion condition, variance was 2.56. After choosing between the sundaes, participants responded to dependent measures and manipulation checks (below), completed a demographic questionnaire, and were dismissed.

To validate our manipulation of taste similarity and examine aspiration levels in the category, a separate pretest was conducted. One hundred twenty-six participants from Mechanical Turk received the taste similarity manipulation described above and then reported the extent to which they thought that the reviewers described had similar tastes in ice cream sundaes were (1 = "not at all similar," 7 = "very similar"). In addition, participants reported the minimum average rating required for an ice cream sundae to enter their consideration set, using a scale of 1–5 "stars." Results confirmed that our taste similarity manipulation was successful: reviewer tastes were perceived to be more similar in the control condition than the taste-dissimilar condition (4.32 vs. 2.91; $F(1, 124) = 28.65$, $p < .001$). In addition, the average reported aspiration level was 3.56 ($SD = .63$), significantly below the 4-star average rating of the target option ($t(125) = -7.83$, $p < .001$).

Purchase Intention. Participants were told to assume that they had received a coupon for a free ice cream sundae at the shop (including any flavor and toppings). Next, they were asked to state their intention to purchase the target option with the coupon on a 7-point scale (1 = "not very likely," 7 = "very likely").

Causal Attribution. In contrast to study 2, attributions for dispersion were measured with two separate items. The first item asked participants to rate the extent to which they believed that product characteristics ("look, flavor, quality, texture, etc.") were important in causing the observed distribution, and the second item asked participants to rate the extent to which reviewer characteristics ("tastes, personalities, individual styles, moods, etc.") were important. Both items utilized 9-point scales (1 = "not at all important," 9 = "very important").

Potential Benefits of Dispersion. A variety of exploratory items were included to examine the possibility that participants would perceive benefits from reviewer-attributed dispersion. The items utilized 5-point Likert scales and included the following: "The product would allow me to learn about my own likes and dislikes within the product category"; "I am curious to know what my experience would be like"; "Trying the product would be an indication that I am open-minded and interesting"; "If I were to try the product and be unsatisfied, I would blame the misleading reviews"; and "If I were to try the product and be unsatisfied, I would blame myself."

Manipulation Checks. As a check of the dispersion manipulation, participants were asked to indicate their perception of ratings in the target WOM distribution, using a scale from 1 ("very spread apart") to 9 ("very close together"). The demographic questionnaire also contained an IMC, identical to that of study 2.

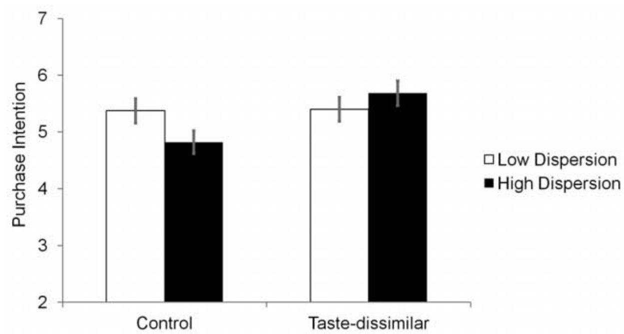
Results

Manipulation Checks. Prior to the analysis, we excluded participants who chose the decoy option ($N = 20$) or failed the IMC ($N = 70$), leaving a usable sample of 242 participants. Examination of the dispersion manipulation check revealed that participants perceived ratings to be closer together in the low-dispersion conditions than the high-dispersion conditions (7.30 vs. 4.34; $F(1, 238) = 79.02$, $p < .001$); main and interaction effects of taste similarity were not significant.

Purchase Intention. The pattern of means for purchase intention is depicted in figure 7. A two-way ANOVA revealed a main effect of taste similarity ($F(1, 238) = 4.38$, $p = .04$), such that intention was higher when reviewers were dissimilar. Most important, and consistent with predictions, analyses revealed a significant dispersion × taste similarity interaction ($F(1, 238) = 3.86$, $p = .05$). Planned follow-up contrasts revealed that in the control conditions, intention was marginally higher when dispersion was low ($M = 5.37$) than when dispersion was high ($M = 4.82$; $F(1, 238) = 3.49$, $p = .06$). However, in the taste-dissimilar conditions, dispersion had no reliable effect on intention ($M_{low} = 5.40$, $M_{high} = 5.68$; $F(1, 238) = 0.86$, NS).

FIGURE 7

STUDY 3: PURCHASE INTENTION AS A FUNCTION OF REVIEWER TASTE SIMILARITY AND WOM DISPERSION



Causal Attribution. To create a relative attribution score, we computed the difference between the two attribution items, so that a higher score indicated greater reviewer (lesser product) attribution. Analysis via ANOVA revealed a main effect of dispersion ($F(1, 238) = 12.02$, $p = .001$), such that participants assigned higher attribution to reviewer causes when dispersion was high than when dispersion was low.

The interaction of dispersion and taste similarity was not significant ($F(1, 238) = 1.34$, NS), although the effect of dispersion was directionally larger in the taste-dissimilar condition ($M_{high} = .02$, $M_{low} = -1.43$, $p < .01$) than the control condition ($M_{high} = 0.03$, $M_{low} = -.70$, $p = .10$).

Potential Benefits of Dispersion. Examination of exploratory items via ANOVA revealed only one item for which responses differed reliably across conditions: "Trying the product would be an indication that I am open-minded and interesting." For this item, participants were significantly more likely to agree when dispersion was high ($M_{high} = 3.50$, M_{low} 3.05; $F(1, 238) = 11.70$, $p = .001$). Moreover, responses to the open-mindedness item were positively correlated with responses to the combined attribution measure ($r = .25$, $p < .001$). Although speculative, this finding suggests for some consumers, reviewer-attributed WOM dispersion may represent an opportunity to signal open-mindedness by trying the product.

Discussion

Study 3 eliminated potential confounds in our prior studies by holding product domain constant and by manipulating taste similarity directly, through the information provided about the individuals underlying the WOM distribution. Results were consistent with our framework and the prior studies: dispersion was perceived negatively when participants were provided no information about taste similarity; however, when participants were led to believe that reviewer tastes were diverse, the negative effect of dispersion was eliminated entirely. In addition, we obtained initial evidence that participants viewed products with diverse reviewers or high-dispersion as an opportunity to appear open-minded and interesting. Building on this finding, our next study explored openness to experience as a potential moderator of our focal effect.

STUDY 4: TASTE SIMILARITY AND OPENNESS TO EXPERIENCE

In our final study, we again manipulated taste similarity while holding the product domain constant. In addition, we expanded on the prior studies by using a product (digital cameras) that is more utilitarian in nature. To manipulate taste similarity, we directly informed participants that the group of reviewers who provided WOM was either highly alike or highly diverse on a variety of different characteristics, including their tastes in the product domain.

In addition, we examined our conceptual model more thoroughly by exploring the role of a theoretically relevant individual difference variable, openness to experience ("openness"). Openness represents one of the "big five" personality dimensions (McCrae 1996) and has been shown to impact a variety of social behaviors and consumer decisions (Kochanska, Kim, and Koenig Nordling 2012; Ratner and Kahn 2002; Thompson and Norton 2011). High openness is characterized by a drive for novel encounters, appreciation of variety, and tolerance of ambiguity; low openness is characterized by a preference for familiarity, conformity, and simplicity.

Thus far, we have argued that consumers are more likely to accept high dispersion when tastes are perceived to be dissimilar, because dispersion is attributed to reviewer differences rather than the product itself. Here we predict that this pattern should be especially likely for consumers high in openness. Results of study 3 suggested that consumers may view products with disperse WOM as an opportunity to appear open-minded and interesting, and this perceived benefit should be especially appealing to high-openness consumers. Therefore, we argue that openness will moderate the influence of attribution on consumer reactions to dispersion. Formally, we predict the following:

> **H3**: The moderating influence of taste similarity on effects of WOM dispersion will be stronger among consumers with greater openness to experience.

Method

Experimental Procedure. Participants were 131 US residents (mean age = 35, 53% female) from the Mechanical Turk platform who received monetary compensation. In the cover story, participants were told that they had received a coupon for a new digital camera that is capable of creating three-dimensional, panoramic images. According to the story, they had visited the retailer's website and located the product page in order to obtain more information.

The study incorporated a between-subjects factorial design, in which WOM dispersion (*low* vs. *high*) was crossed with taste similarity information (*taste similar* vs. *taste dissimilar*), and participants were randomly assigned to one of the four resulting cells. The taste similarity manipulation was administered immediately prior to presentation of the WOM distribution. Participants in the taste-similar conditions were informed that the WOM was provided by reviewers who "have similar backgrounds, personal experiences, etc., and are likely to have very similar tastes in electronic devices." Participants in the taste-dissimilar conditions were informed that the WOM was provided by reviewers who "have a wide range of backgrounds, personal experiences, etc., and are likely to have very different tastes in electronic devices."

As before, the WOM stimuli provided both an overall average rating (on a scale from 1 to 10 stars) and a chart depicting the number of prior reviewers assigning each underlying rating. In all conditions, the distribution included 400 total reviewers, with an average rating of seven stars. The variance of ratings was 0.4 in the low-dispersion conditions and 15.9 in the high-dispersion conditions. After viewing the WOM distribution for the camera, participants responded to the measures below, completed a demographic questionnaire, and were dismissed.

Product Evaluation. Participants were asked to evaluate the digital camera on four, 7-point attitude items: "not at all good—very good," "not at all exciting—very exciting," "not at all favorable—very favorable," "not at all effective—very effective." They also completed the same 7-point purchase intention measure used in studies 2–3. Given the high correlation among these items ($\alpha = 91\%$), they were averaged to create an overall evaluation score.

Causal Attribution. Similar to study 3, product and reviewer attributions were measured separately with two items. The first item asked participants to rate the extent to which product characteristics ("design, performance, quality, etc.") were important in causing the observed distribution. The second item asked participants to rate the importance of personal reviewer characteristics ("personalities, individual styles, moods, etc."). Both items were measured with 9-point scales (1 = "not at all important," 9 = "very important").

Openness. Participants completed 10 items from the openness to experience subscale of the Big Five Inventory (John and Srivastava 1999), for example, "I see myself as someone who is curious about many different things." Agreement with each item was reported on a 5-point scale (1 = "disagree strongly," 5 = "agree strongly").

Manipulation Checks. As a check of the dispersion manipulation, participants were asked to indicate their perceptions of the WOM distribution they were presented, on a scale from 1 (“very spread apart”) to 5 (“very close together”). The demographic questionnaire also contained an IMC identical to that of studies 2–3.

Results

Manipulation Checks. Four participants who failed the IMC were discarded prior to the analysis, leaving a sample of 127 participants. Examination of the dispersion manipulation check revealed that participants perceived WOM distributions to be closer together in the low-dispersion than the high-dispersion conditions (7.77 vs. 2.89; $F(1, 123) = 189.20$, $p < .001$); main and interaction effects of taste similarity were not significant (all $F < 1$).

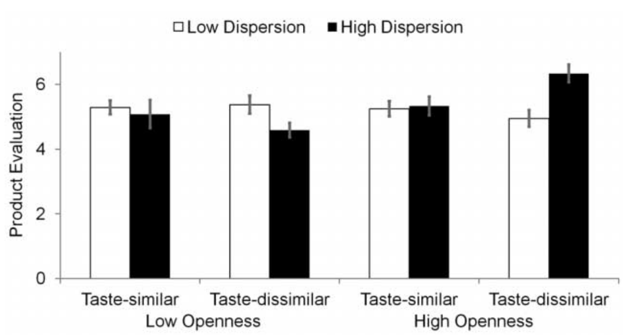
Product Evaluation. In an initial analysis excluding the openness variable, results of an ANOVA revealed no effects of dispersion, taste similarity, or their interaction on overall evaluation. To investigate a model including openness, we regressed product evaluations on dispersion (low = 0, high = 1), taste similarity (similar = 0, dissimilar = 1), openness ($M = 3.75$, SD = .66), and their interactions. As predicted, results revealed a significant dispersion × taste similarity × openness three-way interaction ($B = 1.43$, SE = .64, $p < .05$). In order to identify the range of openness for which the dispersion × taste similarity two-way interaction was significant, we decomposed the interaction using floodlight analysis (Hayes and Matthes 2009; Spiller et al. 2013). Results identified a significant dispersion × taste similarity interaction for participants with an openness score above 4.04 ($B_{JN} = .78$, SE = .39, $p = .05$). In addition, we performed a traditional spotlight analysis at low (−1 SD) and high (+1 SD) levels of openness, with results depicted in figure 8. At 1 SD below the mean of openness, analysis revealed no evidence of a dispersion × taste similarity interaction ($F(1, 119) = .93$, NS). At 1 SD above the mean of openness, however, analyses revealed a significant interaction ($F(1, 119) = 6.23$, $p = .01$). Follow-up comparisons revealed that dispersion did not significantly affect evaluation in the taste-similar conditions (low vs. high dispersion: 5.25 vs. 5.33, $F(1, 119) = .05$, NS) but actually improved evaluations in the taste-dissimilar conditions (4.95 vs. 6.34, $F(1, 119) = 14.02$, $p < .001$).

Causal Attribution. We next explored the evidence for our overall conceptual model, in which attributions differentially mediate the effects of dispersion under different levels of taste similarity and openness. Analysis proceeded in two steps. In the first step, we created a relative attribution score in the same manner as study 3, so that a higher score indicated greater reviewer attribution. Analysis of relative attribution via ANOVA revealed a significant two-way interaction of taste similarity and dispersion ($F(1, 123) = 6.59$, $p < .05$), and follow-up comparisons revealed a pattern consistent with predictions. In the taste-dissimilar conditions, relative reviewer attribution increased from low dispersion to high dispersion (−1.56 vs. .54, $F(1, 123) = 10.27$, $p < .001$). In the taste-similar conditions, however, dispersion had no reliable effect on attribution (−.44 vs. −.75, $F(1, 123) = .21$, NS).

In the second step, we divided participants into low and high levels of openness by use of a median split. For each level of openness, we then conducted a moderated mediation analyses identical to that in study 2. The analysis included dispersion as the independent variable (0 = low, 1 = high), taste similarity as the moderator (0 = taste-similar, 1 = taste-dissimilar), causal attribution as the mediator, and evaluation as the dependent variable. For participants in openness, results of the analysis revealed no evidence of an indirect pathway through attribution ($B = -.11$, SE = .12, 95% CI: −.48, .04). However, for participants high in openness, the indirect pathway through attribution was positive and significant ($B = .44$, SE = .29; 95% CI: .05, 1.21).

FIGURE 8

STUDY 4: PRODUCT EVALUATION AS A FUNCTION OF REVIEWER SIMILARITY AND WOM DISPERSION



NOTE.—Openness was measured using openness to experience subscale of the Big Five Inventory (John and Srivastava 1999). The bars show mean product evaluations estimated by spotlight analysis conducted at low (−1 SD) and high (+1 SD) levels of openness.

Follow-up tests of conditional indirect effects revealed that the effect of dispersion through attribution was significant for taste-dissimilar conditions ($B = .44$, SE $= .25$, 95% CI: .08, 1.06) but was not for taste-similar conditions ($B = .00$, SE $= .14$, 95% CI: $-.29$, .29). Finally, when attribution was controlled for, the direct effect of the taste similarity $\times$ dispersion interaction on evaluations was no longer significant ($B = .53$, SE $= .57$, NS).

Discussion

Study 4 extended our previous findings in two important ways. First, we obtained additional evidence for our attribution mechanism with a different manipulation of taste similarity. Second, we identified the role of a theoretically relevant personality variable, openness to experience. Faced with high WOM dispersion, participants low in openness appeared to simply lower their product evaluations, regardless of the attributions they made for that dispersion. In contrast, participants high in openness responded favorably to dispersion, but only when it could be attributed to reviewers. These results support our broader framework in which the effects of WOM dispersion will depend on its perceived implications within specific decision contexts.

It is noteworthy that when openness was excluded from the analysis, we did not obtain the dispersion $\times$ taste similarity interaction observed in studies 1–3. Given that target evaluations were high across all conditions, one (admittedly speculative) possibility is that the presence of a highly appealing and novel stimulus participants led participants to be especially risk-tolerant.

GENERAL DISCUSSION

Consumers have long been faced with the problem of reconciling mixed opinions about the same product or service. Until recently, however, limited access to WOM meant that disagreement was encountered infrequently and could often be resolved by assessing the credibility of the source: for example, the opinions of a similar friend, a consistent critic, or an expert endorser may be taken more seriously. In contrast, modern online WOM platforms present an immense variety of opinions, provided by largely unknown sources, making such assessment impractical. To help consumers process such abundant WOM information, platforms are increasingly likely to provide summaries in distributional form. The dispersion present in a WOM distribution provides a direct indicator of the extent to which opinions differ, and our research focuses on how consumers respond to this dispersion.

Theoretical Contributions

Although information consistency is a prominent topic within consumer research, there have been relatively few investigations in the WOM context. Most prior research on the effects of WOM dispersion has utilized a reference-dependent paradigm, in which dispersion represents uncertainty regarding the outcome of consumption (Sun 2012; West and Broniarczyk 1998). As a result, the main focus of existing work has been the differential impact of dispersion in loss domains versus gain domains. Supplementing this work, our attribution-based approach provides a new perspective on consumer interpretation of WOM dispersion. We demonstrate that beyond its value as an indicator of potential outcomes, dispersion can serve additional informational and motivational functions, and that a key determinant is the extent to which consumers perceive that individuals contributing WOM have similar tastes. In particular, when tastes are perceived to be very dissimilar, high dispersion is more likely to be attributed to reviewer characteristics, signaling not only increased uncertainty but also increased opportunities. We believe this framework offers new insights into the interpretation and utilization of consumer WOM.

The inclusion of taste similarity as a moderating variable in our framework provides a useful extension to traditional models of consumer attributional inference, in which low consensus is associated with greater external attribution (Folkes 1988). Moreover, our framework may be useful in reconciling mixed findings in the empirical WOM literature. In general, studies identifying a positive influence of dispersion on consumer response have examined products characterized by dissimilar tastes (e.g., fragrances, Moe and Trusov 2011, craft beers; Clemons et al. 2006). Within our framework, it is precisely for such products that high dispersion will tend to be attributed to reviewer causes rather than product causes. In contrast, a negative influence of WOM dispersion has been found in domains characterized by relatively homogenous tastes (e.g., niche video games, Zhu and Zhang 2010). Although the impact of WOM dispersion on sales and related outcomes will be influenced by a range of factors, our findings suggest that taste similarity is an important consideration.

In the study of quality perception and satisfaction, researchers have theorized that uncertainty in consumer expectations can evoke tolerance for inferior consumption experiences (Golder, Mitra, and Moorman 2012; Zeithaml, Berry, and Parasuraman 1996). Our research may help to inform this idea by clarifying the role of uncertainty. Specifically, we suggest that when uncertain expectations for a product are attributed to differences among users rather than the product itself, they represent an opportunity for self-enrichment, curiosity-seeking, or other desirable goals, even if choice of the product experience proves unsatisfactory.

Furthermore, our findings contribute to broader research on positive aspects of disagreement (Boring 1929). For example, Chen and Berger (2013) have shown that individuals are more likely to engage in conversation regarding “controversial” topics because those topics are more intrinsically interesting. In a very different setting, we find that controversy in product evaluations, as represented by WOM dispersion, can be more or less appealing to prospective consumers, depending on its implications. In particular, consumers may be willing to “buy into” products evoking greater disagreement but only when that disagreement cannot be easily resolved (i.e., when it is attributed to differing tastes rather than inconsistent product performance).

Limitations and Future Research

A key assumption in our framework is that WOM dispersion is made salient to potential consumers. In all of our studies, participants received graphical summaries of user ratings, prominently displayed, with little additional information on which to base the decision (especially in studies 1–2). In contrast, real-world platforms vary considerably in the extent to which they make distribution information readily available, prominent, or easy to process. In these settings, consumers may lack the motivation to learn about WOM dispersion or incorporate it into their decision. Both the degree of salience required to observe our effects and the methods by which this salience may be established are worthy of future attention.

Similarly, WOM distributions in our studies were depicted with a horizontal bar chart, and this format is common in real-world implementations. However, both prior research and intuition suggest that physical characteristics of the display will affect perceptions of the distribution (Graham 1937; Schneider and Lopes 1986; Stone et al. 2003). As just an example, merely stretching the display horizontally will magnify differences in the length of each bar and may therefore increase the level of dispersion perceived. More generally, the format of the display (i.e., bar chart, pie chart, etc.) is likely to influence the process by which distributional information is perceived and utilized (Newman and Scholl 2012; Spence 1990). Although we held these characteristics constant in our studies, they merit further exploration.

Considered at the product level, taste similarity overlaps with other popular constructs used to classify consumption experience. In particular, given that utilitarian products tend to be taste similar and hedonic products tend to be taste dissimilar, our work supplements prior research suggesting that attributions for WOM vary across hedonic and utilitarian categories (Sen and Lerman 2007). However, there exist numerous exceptions to the general association of taste similarity and product type; for example, consumers have widely differing preferences in utilitarian categories such as laptops and automobiles, and Gilbert et al. (2009) have demonstrated that preferences in hedonic settings are often surprisingly alike. In the future, it would be interesting to explore potential interactions between these variables. For example, to the extent that consumers with hedonic goals employ subjective standards, they may be especially likely to make reviewer attributions and tolerate high dispersion (Botti and McGill 2011). Along the same lines, products used by consumers to establish their self-identities tend to be taste dissimilar (e.g., music, clothing). Recent research on the motivated consumption of identity-relevant products (Berger and Heath 2007) suggests a number of intriguing ideas regarding the interplay of identity motives and WOM dispersion. For example, dispersion in WOM provided by an aspirational group may reduce the value of a product for identity signaling, lowering its attractiveness.

Although our research focuses on the perceptions of a consumer regarding similarity among a group of reviewers, it would be interesting to consider perceptions regarding his or her own similarity with the group. Consistent with the "assumed similarity" principle in social inference (Cronbach 1955), recent evidence suggests that consumers in ambiguous contexts tend to assume themselves similar to others, and to rely on others' ratings to estimate their own (He and Bond 2013; Irmak, Vallen, and Sen 2010). However, the situation is likely to become more complicated when utilizing group information. In particular, the concept of "consumer-reviewer similarity" is most meaningful when taste similarity is high: if reviewers have widely varying tastes, then there is no single reference to which observers may compare themselves. More general, the relationship between taste similarity and consumer-reviewer similarity merits further exploration.

Our framework conceptualizes taste similarity and dispersion independently, but there are likely to be situations in which WOM dispersion itself evokes inferences regarding taste similarity (e.g., when product knowledge is extremely limited). The interplay of these two variables is an interesting topic for future research. Finally, although variance in graphical WOM distributions provides a direct indication of dispersion, it would be worthwhile to consider other means of making this assessment. For example, consumers given no ratings at all might still estimate dispersion from comments of individual reviewers, the relative "likes" and "dislikes" a product receives, the distribution of sales for products within a category, etc.

Managerial Implications

Having recognized the increasing role of WOM in all aspects of consumer behavior, practitioners have faced a variety of challenges in updating their marketing strategies to reflect modern communications tools. Given these challenges, our work offers useful implications for marketers encountering mixed opinions regarding the products and services they provide. Although intuition may suggest that the uncertainty evoked by polarized WOM will drive away prospective customers, our results indicate that this need not be the case. Instead, the negative impact of WOM dispersion is likely to vary substantially across different consumer and product contexts. In particular, our findings suggest that dispersion is a much more serious concern in taste-similar domains than taste-dissimilar domains, and may even be perceived positively in the latter case.

Beyond simply accepting the consequences of WOM dispersion, our findings suggest various means by which managers may proactively influence the way that dispersion is perceived. For example, in keeping with the taste similarity manipulation of study 3, marketers might strategically implement product or packaging design to signal diversity among consumers of their product. The same signal may be conveyed through various other tools, including communications and messaging (e.g., testimonials or advertisements highlighting a diverse range of users), distribution (utilizing a broad range of retail channels), and so forth. To the extent that these signals are successful, variance in WOM will be attributed to user idiosyncrasies rather than inconsistent product performance, diminishing its likelihood of driving consumers away.

As communication technologies continue to advance, consumers will have ever-expanding access to the opinions of their peers. Accordingly, the distribution of these opinions will play an increasingly important role in consumer judgment and decision making. The presence of mixed voices presents opportunities and challenges for managers and scholars alike, and we look forward to greater understanding of this evolving topic.

DATA COLLECTION INFORMATION

The second author supervised the collection of data for study 1 by research assistants at the Georgia Institute of Technology in the fall of 2013. The first author managed the collection of data for study 2 and study 3 through Amazon Mechanical Turk in the fall of 2012 and the summer of 2014, respectively. The second author managed the collection of data for study 4 through Mechanical Turk in the summer of 2013. All data were analyzed by the first author under the supervision of the second author.

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