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The Effect of the Dispersion of Review Ratings on Evaluations of Hedonic Versus Utilitarian Products

Wujin Chu, Minjung Roh, and Kiwan Park

ABSTRACT: Using the information-diagnosticity framework, this study demonstrates that when exposed to highly versus lowly dispersed ratings, consumers evaluate hedonic products more positively than they do utilitarian products. Three experiments offer evidence to support this prediction, by comparing music files and car navigation devices (Experiment 1), fiction books and driver’s license test preparation books (Experiment 2), and two smartphone apps, a comic book and a voice translator (Experiment 3). Compared to lowly dispersed ratings, highly dispersed ratings improve the evaluation of hedonic products by reducing the perceived uncertainty of how accurately one can predict decision outcomes in terms of achieving the decision goals. The proposed effect also emerges as more pronounced when the average ratings are high rather than low. This observation adds refinements to existing reference-dependent models by showing that the pursuit of hedonic goals reverses general preferences for low over high dispersions of ratings at high average levels. Overall, this study offers an explanation for the previously mixed findings on the effect of the dispersion of review ratings by focusing on the notion of preference heterogeneity, which underlies the difference between hedonic and utilitarian products.

KEY WORDS AND PHRASES: Consumer decision making, consumer preference heterogeneity, decision-making uncertainty, dispersion of reviews, hedonic products, information diagnosticity, online reviews, utilitarian products.

Product evaluations do not always converge across consumers. Some products incur controversy by provoking both support and opposition. For example, Amazon.com reviews for Michael Bay’s film Pearl Harbor include both fervent acclamation and severe condemnation. Some viewers praise the spectacular battle scenes and patriotic messages, yet others denounce the movie’s obsession with soap-operatic sentimentalism. For Lenovo’s Ideapad A1, praise focused on the low price and relatively good quality, whereas criticism pointed out the unreliable Wi-Fi connections of this device. When confronted with these controversies, do prospective consumers enhance or discount their product evaluations?

To address these questions, the present study proposes that the product type—hedonic versus utilitarian—moderates the effect of the dispersion of review ratings (i.e., highly versus lowly dispersed ratings) on product evaluations. This proposition builds on previous works that pertain to inherent differences between hedonic and utilitarian products [5, 48]. Preference heterogeneity is greater for hedonic than for utilitarian products.

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[17, 51]; whereas one single ideal point governs the preferences for utilitarian products such as computers, multiple ideal points govern the preferences for hedonic products such as movies [5, 26, 48]. The information-diagnosticity framework proposes that this perception of multiple ideal points fuels the *positivity effect*, the tendency of viewing positive ratings as more diagnostic than negative ratings [17, 19, 20, 21, 62]. Because a positive rating occurs only when a product matches a reviewer’s intended ideal point, whereas a negative rating occurs either when it uniformly mismatches all of the ideal points or when it improperly “matches” an ideal point other than the reviewer’s intended ideal point, positive ratings ensure more diagnostic predictions of product outcomes [25, 34]. Therefore, the assessment of highly dispersed ratings for hedonic products depends more on positive than on negative ratings [27, 54]. However, for utilitarian products, where one single ideal point guides consumer preferences, such positivity effects will not be observed; instead, the negativity effect will predominate because even one single negative rating can undermine product evaluations by indicating poor reliability in product performance. Hence, exposed to highly dispersed ratings, consumers are likely to evaluate hedonic products more favorably than utilitarian products.

To examine this prediction in depth, this study investigates the three-way interaction among the product type, the dispersion of review ratings, and the valence of review ratings, whereas prior studies have focused on subsets of these three factors [31, 37, 44, 51, 56, 61]. To date, most prior research indicates that at high average ratings, safer, lowly dispersed ratings appear preferable to riskier, highly dispersed ratings, in accordance with the reference-dependent model [37, 61]. The present article shares with this line of research the idea that the relative merit of less risky options increases with high rather than low average ratings. Yet, this article differs from these works in that it postulates that what options are perceived as riskier depends on what types of goals are pursued. Because the pursuit of hedonic goals incurs a positivity effect through the perception of multiple ideal points, highly dispersed ratings likely appear more diagnostic and help reduce risk in purchase decisions [17, 19, 20, 21, 62]. The typical risk averseness at higher average ratings—a tendency predicted by the reference-dependent model—therefore may translate into a greater preference for products with safer, highly dispersed ratings for hedonic products [29, 61]. However, when utilitarian goals are focal, and the negativity effect predominates, such risk averseness at higher average ratings may instead manifest as a preference for lowly dispersed ratings.

As another contribution to the extant literature, the current paper also investigates the underlying mechanism behind the interaction between product type and the dispersion of review ratings by highlighting the mediating role of decision-making uncertainty. A key argument made here is that consumers should experience higher uncertainty if the review information with which they make purchase decisions does not ensure accurate diagnosis regarding decision outcomes [23, 41, 46]. Because the pursuit of hedonic goals raises the perception of multiple ideal points, highly dispersed ratings appear more diagnostic and helpful for reducing the uncertainty in decision-making processes [12, 17, 21, 41, 48]. Yet, for utilitarian goals for which consumers generally share their ideal
prototypes, lowly dispersed ratings are likely to alleviate such uncertainty by incorporating high reliability in performance. Therefore, the uncertainty involved in decisions made based on highly dispersed ratings is likely to be lower for hedonic than for utilitarian products, thereby eliciting more favorable product evaluations with such ratings from hedonic than from utilitarian products [22].

The next section reviews the literature that pertains to the dispersion of review ratings, distinctions between hedonic and utilitarian products, the role of average ratings, and decision-making uncertainty. The same section then presents the main hypotheses, tested in three experimental studies. Experiment 1 provides evidence in support of the predicted interaction between product type and the dispersion of review ratings. Experiment 2 investigates whether this interaction effect is more pronounced at high rather than low average ratings. Experiment 3 tests the mediating role of decision-making uncertainty as the proposed underlying process. Finally, this article concludes with theoretical and managerial implications of these findings, along with some limitations.

**Theoretical Background and Hypotheses**

**Dispersion of Review Ratings: Highly versus Lowly Dispersed Ratings**

Prior research offers mixed findings about the effect of high versus low dispersions of ratings. Generally, consumers avoid risk; disagreements (i.e., highly dispersed ratings) should have a negative influence on demand. Sales data on books from Amazon.com and game titles from Gamespot.com support this proposition [14, 66]. Conversely, disagreements can attract consumers by stimulating debate [6]. Differences in opinions motivate people to engage in fierce discussions, increasing the volume of word of mouth and, ultimately, sales [11, 30]. In brief, highly dispersed ratings can be a mixed blessing for marketers.

Prior literature suggests some moderating factors to explicate the mixed findings. Borrowing the concept of consumers’ aspiration levels from Kahneman and Tversky’s [29] prospect theory, West and Broniarczyk [61] demonstrated that highly dispersed ratings have nonnegative effects on products that fall short of aspiration levels but negative influences when the product exceeds the aspiration level [37]. Park and Han [44] indicated that highly dispersed ratings negatively influence evaluations of search goods such as MP3 players but positively influence evaluations of experience goods such as cosmetics, especially if consumers have favorable prior brand attitudes.

In general, responses to highly dispersed ratings are more positive for hedonic than for utilitarian products, as shown in Table 1. Hedonic products such as movies [30, 31], fiction [11], and craft beer [12] prompt positive or nonnegative responses to highly dispersed ratings. Conversely, utilitarian products or services such as MP3 players [44] and stock investments [36]
reveal a negative relationship between highly dispersed ratings and consumer responses. However, a few caveats are worth noting. First, some literature indicates negative effects of highly dispersed ratings, even for hedonic products [66].
Yet this finding has applied only to less popular brands. Perhaps low popularity decreased consumers’ aspiration levels enough that these respondents became more risk prone, favoring riskier, lowly dispersed ratings over safer, highly dispersed ratings in choosing hedonic products [61]. Second, studies that use coffee as an experimental stimulus reveal no significant effects of highly dispersed ratings [8, 13]; perhaps coffee’s ambiguous position on the hedonic–utilitarian spectrum [42, 64] blurred the effects of highly dispersed ratings.

Third, some practices in previous research, such as pooling data from various categories [14, 39, 56], may prevent focused contrasts between hedonic and utilitarian products. For example, the findings related to hotel reviews seem uncertain [49, 63] because the studies included both hedonic (leisure hotels) and utilitarian (business hotels) subcategories. Fourth, studies focused on hedonic products such as cosmetics reveal that positive responses to highly dispersed ratings might emerge only when participants hold favorable prior attitudes [44]. Utilitarian products instead yield consistently negative responses to highly dispersed ratings, regardless of consumers’ prior attitudes.

To establish clear causality, this research investigates the effect of the dispersion of review ratings by formally contrasting hedonic with utilitarian products in three controlled experiments. To minimize potential contaminations, these studies also control for confounding variables and apply the same product category to both hedonic and utilitarian conditions (Experiments 2 and 3), using two different genres of book titles and smartphone apps, rather than different product categories.

**Hedonic Versus Utilitarian Products and Preference Heterogeneity**

Consumer behavior literature identifies two distinct motivations for shopping [5]. Utilitarian benefits usually result from a conscious pursuit of intended practical consequences; utilitarian consumption is more task related, instrumental, rational, and relevant to a work mentality. Conversely, hedonic benefits derive from spontaneous affective responses; hedonic consumption relates more to fantasy, escapism, arousal, sensory attributes, and a play mentality [5, 26]. Product evaluations along the hedonic dimension therefore tend to reflect divergent criteria across different consumers, whereas evaluations of utilitarian products rely mainly on well-defined criteria that most consumers accept [26].

To capture such distinctions, the present research relies on the notion of *preference heterogeneity*, or the extent to which people’s preferences for products vary [48]. High-preference heterogeneity implies substantial variations in consumer tastes, low consensus across consumers, and many distinct clusters of ideal points in the attribute space. Low-preference heterogeneity instead denotes minimal variations in consumer preferences, manifested as high-consensus and tightly clustered ideal points in the attribute space [17]. Previous literature cites a positive correlation between hedonic (utilitarian)
consumption and high-preference (low-preference) heterogeneity for hedonic (utilitarian) products, such as nightclubs, restaurants, and hair salons (plumbers, rug cleaners, and auto mechanics) [17].

Interaction Between Product Type and the Dispersion of Review Ratings

The current research draws on the notion of information diagnosticity to predict the interaction between product type and the dispersion of review ratings. The information-diagnosticity framework posits that information capable of discriminating well between alternative products is deemed highly diagnostic [34]. Diagnostic information helps to discriminate between good and bad products in terms of meeting one’s decision goals [41, 60]. Consumers can reach more accurate predictions of whether the product fits their focal goals well using this type of information [25, 34]. The typical negativity effect conceptually builds on this theoretical approach. Because most products are associated with positive attributes, negative information makes it easier to discriminate one product from another, ensuring a more accurate judgment of product outcomes [25, 51, 54]. For this reason, consumers weight negative information more heavily than neutral or positive information when making a purchase decision.

An important question to address is whether this negativity effect applies, as is, to the context of online peer ratings. One feature of this context is that the reviewers, the sources of review ratings, exist as anonymous others. Explicit knowledge about the similarity between reviewers and oneself is hardly apparent in this context. A reasonable clue to determine how much the ratings deserve to be referred to as a guide for one’s decision making thus likely comes from the perception of preference heterogeneity. In this respect, the occurrence of the negativity effect will also likely depend on the perception of preference heterogeneity. That is, under low perceived preference heterogeneity, others’ negative ratings are likely to be accepted as the proper proxy for negative outcomes for oneself. Products with which reviewers have had bad experiences indeed should also work poorly for oneself [43, 51]. However, under high perceived preference heterogeneity, such negative effects may not arise. Products eliciting negative ratings from reviewers may not necessarily work poorly for consumers who perhaps have different preferences from the reviewers.

Furthermore, the inference is warranted that under high perceived preference heterogeneity, such as when hedonic goals are focal, the negativity effect may yield to the positivity effect. High preference heterogeneity essentially reflects multiple ideal points, rather than a single one, across consumers [17]. Positive ratings signify a correct match with one of these ideal points, but negative ratings do not necessarily signify a uniform mismatch with all of the ideal points. It is at most the product’s failure to meet all of the reviewers’ ideal points that can be inferred from such negative ratings. Consumers indeed are not quite certain whether the product is well suited to match their own ideal points or not. More simply, although a positive
rating occurs only when a product matches a reviewer’s intended ideal point, a negative rating occurs either when it uniformly mismatches all the ideal points or when it improperly “matches” an ideal point other than the reviewer’s intended ideal point. Thus, for hedonic products, negative ratings are subject to different interpretations, indicating that there are more ways to create negative ratings than to create positive ratings. Evidence for this positivity effect under hedonic goals actually has been provided in the recent literature [19, 20, 21, 62]. Using review ratings regarding restaurants, movies, movie posters, and ice cream sundaes, these studies have shown that positive information counts as more diagnostic than negative information.

For utilitarian products, however, this positivity effect may not be observed. Due to the convergence of ideal points, whether this single ideal point is reached or not will uniquely determine likes or dislikes. Possible ways of interpreting negative ratings thus would not be more varied than the number of ways used to interpret positive ratings. Instead, the presence of negative ratings signifies low reliability in product performance. Reliability is one of the important virtues to be achieved to fulfill functional needs [5, 26]. Consumers indeed do not simply expect a product to perform well, but to perform “consistently” well across reviewers. Thus, for utilitarian products, even one single negative rating can undermine product evaluations by indicating poor reliability in performance. Negative ratings accordingly should serve as more diagnostic cues to assess reliability for utilitarian products [43, 51, 54].

To summarize, because hedonic goals exhibit higher preference heterogeneity than utilitarian goals and prompt the perception of multiple ideal points, positive ratings should be deemed more diagnostic and weighted more heavily than negative ratings when assessing a high dispersion of ratings [27, 54]. As such, the assessment of highly dispersed ratings is more favorable to evaluations of hedonic products than utilitarian products. This positivity effect, however, is not likely to emerge for utilitarian goals, for which the notion of a convergent ideal point predominates. Stated formally:

**Hypothesis 1.** When reading high versus low dispersions of ratings, consumers evaluate hedonic products more favorably than they do utilitarian products.

**Role of Average Review Ratings**

In general, high dispersions of ratings appear preferable when average ratings are low, but low dispersions of ratings seem preferable when average ratings are high, according to the reference-dependent model [29, 37, 56, 61]. The underlying logic is that people seek more risk when average ratings fall below an aspiration level, but they exhibit more risk aversion when average ratings are higher than this level. This logic is directly relevant to the case of utilitarian products, for which increased risk averseness (risk proneness) at high (low) average ratings leads to
enhanced (reduced) aversion to riskier, higher dispersions of ratings. Because high dispersions of ratings raise concern about product reliability for these products, higher average ratings should increase one’s preference for less risky, lower dispersions of ratings.

For hedonic products, however, this logic implies that the relative merit of high dispersions of ratings increases with high average ratings, because high, rather than low, dispersions of ratings help reduce the risk involved in purchase decisions. To elaborate, risk perception increases when uncertainty is perceived as high [24, 46, 52]. The perceived uncertainty herein refers to the degree to which predictions regarding a decision outcome are not accurately made [46]. Diagnostic reviews help reduce the perceived risk by providing accurate information regarding the traits of a product [23, 24, 41]. Thus, given that positive ratings provide greater diagnosticity about whether to fulfill one’s decision outcomes when multiple ideal points are present, highly dispersed ratings that cover such positive ratings likely ensure lower risk in purchase decisions than lowly dispersed ratings. The previous reference-dependent model accordingly should hold, such that increased risk averseness at high average ratings leads to enhanced preferences for products with safer, highly dispersed ratings, whereas the increased risk proneness at low average ratings leads to reduced preferences for such products [29, 61].

To summarize, although the relative merit of less risky alternatives does constantly increase with high rather than low average ratings regardless of one’s consumption goals, what specific alternatives are perceived as riskier should depend on what goals are pursued. That is, which consumption goal is pursued guides the differential diagnosticity of positive against negative ratings, which in turn directs whether highly or lowly dispersed ratings count as riskier. The pursuit of hedonic goals in this respect should prompt the perception of lower risk with highly dispersed ratings, whereas the pursuit of utilitarian goals does so with lowly dispersed ratings. Therefore, when hedonic goals are pursued, reversed preferences for highly over lowly dispersed review ratings are likely more pronounced at higher rather than lower average levels. Stated more formally:

**Hypothesis 2.** The interaction effect predicted in H1 is more pronounced at high than low average ratings, such that the tendency of high (low) dispersions of ratings to increase evaluations of hedonic (utilitarian) products is more pronounced for high than low average ratings.

**Mediating Role of Decision-Making Uncertainty**

To shed more light on the foregoing propositions, the present study also investigates the underlying mechanism behind the interaction between product type and the dispersion of review ratings, with particular emphasis on the mediating role of decision-making uncertainty. The basic premise is that the uncertainty involved with decisions made based on
highly or lowly dispersed ratings differs for hedonic and utilitarian goals, and this differential uncertainty determines product evaluations. This idea of uncertainty mediation in decision making is well documented in the literature [22, 57].

Thus far, it has been demonstrated that the perceived uncertainty declines with diagnostic information that ensures more accurate predictions of product outcomes [23, 41]. Consumers often rely on diagnostic cues to redress such uncertainty that hinders their decision-making process [24]. For instance, they utilize diagnostic information more heavily when they encounter high uncertainty about whether a product will perform as expected [24] or whether a transaction will proceed as promised [46].

To position this idea in the present context, when review information appears to ensure an accurate diagnosis regarding a purchase decision outcome, consumers may perceive a low level of uncertainty. This lower level of perceived uncertainty then likely boosts the evaluation of the target product [22]. More specifically, the pursuit of hedonic goals tends to facilitate the perception of multiple ideal points for which high dispersions of ratings better ensure greater diagnosticity and lower uncertainty during purchase decisions [12, 17, 21, 41, 48]. Therefore, the uncertainty involved in such decisions is likely to be lower when the decision is made based on high rather than low dispersions of ratings. In contrast, for utilitarian goals, in pursuit of which consumers generally share their ideal prototypes, low dispersions of ratings are more likely to alleviate such uncertainty by incorporating high reliability in performance. Overall, these differential levels of uncertainty between hedonic and utilitarian goals are likely to prompt more favorable evaluations, with higher dispersions of ratings for hedonic than for utilitarian products. Stated more formally:

**Hypothesis 3.** The perceived decision-making uncertainty mediates the interaction between product type and the dispersion of review ratings on product evaluations.

**Experiment 1**

Experiment 1 examines the hypothesized interaction between product type and the dispersion of review ratings (H1). For this analysis, bipolar ratings represent highly dispersed ratings, whereas unanimous ratings proxy for lowly dispersed ratings. Music files and car navigation devices serve as the focal hedonic and utilitarian products, respectively.

**Pretest**

The pretest examined the possible presence of any confounds. Car navigation devices usually cost more than music files, so significant differences might mark consumers’ involvement or subjective knowledge [18, 35]. Forty-eight
undergraduate and graduate students participated and received a random assignment to a condition (22 women, 3 graduate students, $M_{age} = 22.33$). These respondents indicated product involvement ($\alpha = .71$), subjective knowledge ($\alpha = .91$), and prior category attitudes ($\alpha = .97$) toward music files and car navigation devices, in response to test questions (see Appendix A for the measures). A one-way analysis of variance (ANOVA) showed no significant differences between the two product categories ($F_s < 1.60$, $p_s > .20$; $M_{music} = 4.17$, $M_{navigation} = 3.47$ for involvement; $M_{music} = 3.28$, $M_{navigation} = 2.82$ for subjective knowledge; $M_{music} = 5.97$, $M_{navigation} = 5.86$ for prior category attitudes).

**Participants and Design**

A 2 (product type: hedonic vs. utilitarian) × 2 (dispersion of review ratings: high vs. low) × 2 (order of presentation: highly dispersed ratings first vs. lowly dispersed ratings first) mixed design, in which the dispersion of review ratings was a within-subjects factor, was used. Seventy undergraduate and graduate students from the same subject pool as the pretest participated (30 women, 6 graduate students, $M_{age} = 22.16$).

**Stimuli and Procedure**

The participants randomly assigned to the hedonic condition evaluated two fictitious music files, and the respondents randomly assigned to the utilitarian condition evaluated two car navigation devices. The identifiers of the two alternatives within each condition used hypothetical product titles and artist or manufacturer names, which participants read were available in the market (Appendix B). The focal manipulation of these alternatives then indicated whether the review ratings were lowly or highly dispersed. Lowly dispersed alternatives received all ten three-star ratings; highly dispersed alternatives received five one-star ratings and five five-star ratings (Appendix C). The order of presentation of two alternatives was counterbalanced. After being exposed to the review information, participants provided their product attitudes and then completed the section that contained manipulation checks for product type and demographic variables.

**Measures**

Participants provided their product attitudes on three nine-point scales: “I have a good feeling for . . .” “I am interested in . . .” and “I am attracted to . . .” (1 = “not at all,” 9 = “very much so”) [16, 40, 50]. The manipulation check for product type used three seven-point bipolar items [5, 59]: “is related to amusement/practicality,” “helps divert me/promotes instrumental convenience,” and “is beneficial for my leisure
time/enhances work efficiency.” Lower scores indicated more hedonic products.

**Results**

The manipulation check for product type, using a one-way ANOVA ($\alpha = .89$), indicated that music files related more closely to hedonic goals than navigation devices ($M_{\text{music}} = 2.38, M_{\text{navigation}} = 5.76; F(1, 68) = 284.13, p < .01$). Regarding the potential influence of an order effect on product attitudes, a $2 \times 2 \times 2$ (product type) × (dispersion of review ratings) × (order) mixed ANOVA with product attitudes ($a_{\text{low dispersion}} = .86, a_{\text{high dispersion}} = .91$) indicated no significant order effects ($F$s < 1.0, $ps > .30$). Thus, the subsequent analyses collapsed the data across the two order conditions.

A $2 \times 2$ (product type) × (dispersion of review ratings) mixed ANOVA for product attitudes showed a significant main effect of the dispersion of review ratings ($F(1, 68) = 7.04, p = .01$). Regardless of product type, more favorable product attitudes arose when the product ratings were highly rather than lowly dispersed ($M_{\text{low dispersion}} = 4.70, M_{\text{high dispersion}} = 5.43$). The predicted interaction between product type and the dispersion of review ratings qualified this main effect ($F(1, 68) = 4.54, p < .05$). According to planned contrasts, participants expressed more favorable attitudes toward hedonic products when reading highly rather than lowly dispersed ratings ($M_{\text{low dispersion}} = 4.34, M_{\text{high dispersion}} = 5.70; t(33) = -3.92, p < .01$). For utilitarian products, attitudes did not vary as a function of the dispersion of review ratings ($M_{\text{low dispersion}} = 5.04, M_{\text{high dispersion}} = 5.19; t(35) = -.34, p > .70$).

**Discussion**

Consistent with H1, high versus low dispersions of ratings increased participants’ product evaluations for hedonic products, but not for utilitarian products. This study also sought to address some potential confounding effects by showing that involvement, subjective knowledge, and prior category attitudes did not vary across the two focal categories. However, no direct evidence confirmed differential preference heterogeneity across the two product types. Furthermore, other unintended effects across the two categories might have influenced the results. To address these issues, Experiment 2 uses stimuli products from a single category that covers a broad hedonic–utilitarian spectrum. Additional measures also assess familiarity and regulatory focus as potential confounds.

**Experiment 2**

The purpose of Experiment 2 is threefold: (1) to measure perceived preference heterogeneity between hedonic and utilitarian products; (2) to use two different genres of books, rather than different products categories, to
establish causality more clearly; and (3) to accommodate three levels of average ratings to confirm if the proposed interaction between product type and the dispersion of review ratings becomes more pronounced at higher average ratings (H2).

**Participants and Design**

The test featured a 2 (product type: hedonic vs. utilitarian) × 2 (dispersion of review ratings: high vs. low) × 3 (average rating: two, three, or four stars) between-subjects design. Two hundred thirty-nine undergraduate and graduate students from a large university (25 women, 4 graduate students, \( M_{\text{age}} = 23.77 \)) participated.

**Stimuli and Procedure**

Participants considered a fiction book (a hedonic product) or a test preparation book for passing a driver’s license test (a utilitarian product). Both hypothetical titles featured similar product specifications and the same manipulation of review ratings as used in Experiment 1, except that the average ratings were extended to span three levels of average ratings (Appendices B and C). Participants indicated their product attitudes after reading these fictitious product specifications and review ratings. Then, they completed questions pertaining to the manipulation checks, a measure of preference heterogeneity, five confound checks, two ancillary variables, and demographic information.

**Measures**

With its focus on a single product category, this study used a standard measurement instrument to assess product attitudes: four nine-point bipolar scales anchored by “bad/good,” “unpleasant/pleasant,” “undesirable/desirable,” and “unfavorable/favorable” [2, 51]. To check the product-type manipulation, three nine-point bipolar scales used anchors of “emotional/logical,” “amusement/practicality,” and “leisure time/work efficiency” [5, 55, 59]. Regarding the measure of preference heterogeneity, three nine-point Likert scales assessed participants’ responses to the following prompt: “Tastes are important in how people choose . . .,” “Preferences are important in how people choose . . .,” and “For . . ., individuals look for different things” (1 = “not at all,” 9 = “very much so”) [48].

In addition, the five confound checks assessed product involvement, subjective knowledge, product familiarity, and two regulatory foci (Appendix A). Subsequently, two ancillary checks measured prior online shopping experience and the possession of a driver’s license (Appendix A).
Results

Confound Checks and Ancillary Variables

To investigate possible differences in confound checks and ancillary measures across the manipulations, a 2 (product type) × 2 (dispersion of review ratings) × 3 (average rating) ANOVA included product involvement (α = .84), subjective knowledge (α = .72), perceived familiarity, promotion and prevention focus, and online shopping experiences (α = .79) as the dependent variables. None of the effects was significant (Fs < 2.71, ps > .10). Similarly, a logit analysis of possession of a driver’s license revealed no significant treatment effects (Wald χ²s < 2.76, ps > .23).

Manipulation Check and Preference Heterogeneity

A 2 (product type) × 2 (dispersion of review ratings) × 3 (average rating) ANOVA on the manipulation check for product type (α = .87) revealed that the fiction book aligned more closely with hedonic goals than did the test preparation book (Mfiction = 3.62, Mtest = 7.25; F(1, 227) = 495.57, p < .01; all other effects: Fs < 1.95, ps > .14). The same three-way ANOVA for preference heterogeneity (α = .79) then also showed that preferences seemed more heterogeneous for the fiction book than for the test book (Mfiction = 7.34, Mtest = 6.30; F(1, 227) = 29.17, p < .01; all other effects: Fs < 1.20, ps > .30).

Product Attitudes

First, a 2 (product type) × 2 (dispersion of review ratings) × 3 (average rating) ANOVA on product attitudes (α = .82) revealed a significant main effect of average rating (Mtwo = 4.09, Mthree = 5.10, Mfour = 5.72; F(2, 227) = 37.88, p < .01) and a two-way interaction between product type and the dispersion of review ratings (F(1, 227) = 20.88, p < .01). Participants exposed to the fiction book reported more positive attitudes when faced with highly rather than lowly dispersed ratings (Mlow dispersion = 4.55, Mhigh dispersion = 5.19; F(1, 227) = 7.99, p < .01), whereas those exposed to the test book reported the opposite (Mlow dispersion = 5.46, Mhigh dispersion = 4.68; F(1, 227) = 13.32, p < .01).

Both effects showed the qualification of the (marginally) significant three-way interaction (F(2, 227) = 2.86, p = .059); no other effects emerged as significant (Fs < 2.70, ps > .10). The next step involved examining simple interactions between product type and the dispersions of review ratings at each average level. Consistent with H2 (Figure 1), the simple interaction was not significant in the two-star condition (F(1, 227) = .60, p > .40). Tests of simple effects to compare high with low dispersions of ratings were not significant for either the fiction book (Mlow dispersion = 3.99, Mhigh dispersion = 4.16; F(1, 227) = .19, p > .65) or the test book (Mlow dispersion = 4.23, Mhigh dispersion = 3.98; F(1, 227) = .46, p > .45).
However, the simple interaction emerged as significant for both the three-star ($F(1, 227) = 9.23, p < .01$) and the four-star ($F(1, 227) = 16.98, p < .01$) conditions. The planned contrasts indicated that participants in the highly-dispersed-ratings condition reported more favorable attitudes toward the fiction book than those in the lowly-dispersed-ratings condition. These results remained consistent in the three-star ($M_{low\ dispersion} = 4.55, M_{high\ dispersion} = 5.39; F(1, 227) = 4.98, p < .05$) and four-star ($M_{low\ dispersion} = 5.05, M_{high\ dispersion} = 5.91; F(1, 227) = 5.28, p < .05$) conditions. Conversely, participants who considered the test book reported opposite responses in both the three-star ($M_{low\ dispersion} = 5.61, M_{high\ dispersion} = 4.84; F(1, 227) = 4.26, p < .05$) and the four-star ($M_{low\ dispersion} = 6.61, M_{high\ dispersion} = 5.29; F(1, 227) = 12.46, p < .01$) conditions.

**Discussion**

Overall, the results of Experiment 2 support the counterintuitive contention that general preferences for lowly dispersed ratings at high average ratings reverse into a preference for highly dispersed ratings when consumers pursue hedonic goals. More specifically, Experiment 2 extends the findings from Experiment 1 in three ways. First, the relative merit of highly dispersed ratings for hedonic versus utilitarian products grow more pronounced at higher average ratings, as a significant three-way interaction revealed (H2). Second, it confirms explicitly that consumer preferences are more heterogeneous for hedonic than for utilitarian products. Third, by using two book genres as the target products, rather than different product categories,
Experiment 2 reduces the possible confounding effects due to inherent differences across product categories.

**Experiment 3**

Experiment 3 tests the mediating role of decision-making uncertainty as the proposed underlying process explanation behind the interaction between product type and the dispersion of review ratings (H3). To test this mediating effect, Experiment 3 follows the same procedure as Experiments 1 and 2, but with the following three adjustments: (1) online access via smartphones provides a link to the experimental stimuli; (2) the review volume, or the number of reviews, increases to twenty ratings; and (3) the dispersion of review ratings is less extreme and more realistic, such that two reviews deviate from each of the unanimous or bipolar distributions. The focal products are a comic book app (hedonic) and a voice translator app (utilitarian), with smartphone app stores as a simulated online shopping platform.

**Participants and Design**

The experiment used a 2 (product type: hedonic vs. utilitarian) × 2 (dispersion of review ratings: high vs. low) between-subjects design. Ninety-four undergraduate students from a large university participated for partial course credit (55 women, \( M_{\text{age}} = 23.09 \)). All participants reported that they owned smartphones.

**Stimuli and Procedure**

The study was administered online, using a mobile Web browser. The experimental stimuli appeared in fictitious smartphone app stores, onto which participants logged in using their own smartphones. On the Web site, they saw a comic book app or a voice translator app, depending on their randomly assigned condition (Appendix B). The review ratings varied as a function of the study manipulation, similar to the manipulations in Experiments 1 and 2. However, the number of ratings increased from ten to twenty, and the dispersion of the ratings was less extreme, such that the lowly dispersed ratings comprised eighteen three-star ratings, one two-star rating, and one four-star rating, whereas the highly dispersed ratings comprised nine one-star ratings, nine five-star ratings, one two-star rating, and one four-star rating (Appendix C). After browsing these app specifications and review information, participants provided their evaluations of the focal app and their accompanying levels of decision-making uncertainty. Then they completed the manipulation checks, a measure of preference heterogeneity, confound checks, and three ancillary variable measures, including smartphone usage patterns. Finally, they provided demographic information and were debriefed.
**Measures**

The assessments of attitudes toward the apps used the same items from Experiment 2, except that instead of “desirable,” they measured whether the apps were “satisfactory” [2]. Measurements of purchase intentions were also included as another proxy for the product evaluation; they consisted of two nine-point scales anchored by “unlikely to purchase/likely to purchase” and “improbable to purchase/probable to purchase” [9].

The conceptualization of decision-making uncertainty was then derived from the notion of how accurately one can predict decision outcomes in terms of achieving the decision goals [3, 41, 52, 60]. To operationalize such a conceptualization, the measure of decision-making uncertainty used a set of items adapted from Ashill and Jobber [3] and Duncan [15], with an emphasis on the adequacy of review information in reducing uncertainty. The adequacy of information is one of the important dimensions of uncertainty [33, 52], and it is particularly relevant to the current research in that it operationalizes the diagnosticity of review information in light of its adequacy to meet the focal goal [1, 41]. Two items accordingly constituted this measure: “I believe that the given review information about this app is adequate for producing decision outcomes that fit my preferences,” and “I think that the purchase decision based on this review information about the app would lead to better outcomes that suit my preferences well” (1 = “strongly disagree,” 9 = “strongly agree”). These items were reverse-coded; thus, the higher these scores, the higher the level of uncertainty.

In addition, measures of the manipulation check for product type, preference heterogeneity, confound checks (i.e., product involvement, subjective knowledge, familiarity, and two regulatory foci), and an ancillary check (i.e., prior online shopping experiences) were all measured using the same instruments as in Experiment 2. The check of individual smartphone usage patterns also comprised three indicators: the type of smartphone used, the smartphone usage period, and the smartphone usage frequency (Appendix A).

**Results**

**Descriptive Summary of Individual Smartphone Usage Pattern**

Regarding the type of smartphones used, 28 percent of the participants (n = 26) indicated they used iPhones; the remaining 73 percent (n = 68) reported using Android phones. Their smartphone usage periods primarily spanned one to four years; 10 percent of participants reported they had been using a smartphone for less than 1 year, 83 percent reported one to four years, and 7 percent reported more than 4 years. The average smartphone usage frequency was 7.70 on the nine-point scale.
Confound Checks and Ancillary Variables

As in Experiment 2, five variables could have potential confounding effects: involvement ($\alpha = .73$), subjective knowledge ($\alpha = .74$), perceived familiarity, and promotion and prevention focus. A 2 (product type) × 2 (dispersion of review ratings) ANOVA used them as dependent variables but revealed no significant effects ($Fs < 1.45, ps > .20$). Likewise, the three ancillary measures—online shopping experiences ($\alpha = .84$), smartphone usage period, and smartphone usage frequency—revealed no significant differences across conditions ($Fs < 1.50, ps > .30$). None of the significant treatment effects were found in a logit analysis of the type of smartphone used (Wald $\chi^2$s < .50, $ps > .60$).

Manipulation Check and Preference Heterogeneity

A 2 (product type) × 2 (dispersion of review ratings) ANOVA on the manipulation check for product type ($\alpha = .85$) showed that the comic book app aligned more closely with hedonic goals than did the voice translator app ($M_{\text{comic}} = 3.07, M_{\text{voice}} = 6.50; F(1, 90) = 155.06, p < .01$; all other effects: $Fs < .35, ps > .50$). A parallel ANOVA for preference heterogeneity ($\alpha = .74$) also confirmed that preferences seemed more heterogeneous for the comic book app than for the voice translator app ($M_{\text{comic}} = 6.60, M_{\text{voice}} = 5.90; F(1, 90) = 5.28, p < .05$; all other effects: $Fs < .20, ps > .65$).

Product Evaluation

The average scores of attitudes and purchase intentions served as a measure of product evaluation due to their high correlation ($\alpha = .83, r = .57, p < .001$) [28]. A 2 (product type) × 2 (dispersion of review ratings) ANOVA run on this evaluation index revealed a similar pattern of results as in previous experiments; only a significant interaction emerged ($F(1, 90) = 10.11, p < .01$; all other effects: $Fs < 2.45, ps > .10$), and the simple effects analyses confirmed more positive product evaluations with high versus low dispersions of ratings for the comic book app ($M_{\text{low dispersion}} = 3.17, M_{\text{high dispersion}} = 4.51; F(1, 90) = 11.73, p < .01$), but not for the voice translator app ($M_{\text{low dispersion}} = 4.36, M_{\text{high dispersion}} = 3.90; F(1, 90) = 1.26, p > .25$; Figure 2).

Decision-Making Uncertainty

A 2 (product type) × 2 (dispersion of review ratings) ANOVA on decision-making uncertainty ($\alpha = .91$) indicated a significant interaction between product type and the dispersion of review ratings ($F(1, 90) = 7.74, p < .01$; all other effects: $Fs < .80, ps > .35$). Simple effects analyses showed that
participants exposed to the comic book app exhibited a lower level of decision-making uncertainty when reading high versus low dispersions of ratings \( (M_{\text{low dispersion}} = 5.54, M_{\text{high dispersion}} = 4.56; F(1, 90) = 4.30, p < .05)\), whereas those exposed to the voice translator app revealed the exact opposite pattern, albeit at a marginally significant level \( (M_{\text{low dispersion}} = 4.30, M_{\text{high dispersion}} = 5.22; F(1, 90) = 3.48, p = .065; \text{Figure 2})\).

**Figure 2. Product Evaluation and Decision-Making Uncertainty as a Function of Product Type and the Dispersion of Review Ratings (Experiment 3)**

**Mediating Role of Decision-Making Uncertainty**

To test the mediating role of decision-making uncertainty, a bootstrapping analysis was performed adopting the PROCESS macro for SPSS (5,000...
bootstrap samples) [47]. The bootstrap analyses showed that only the inter-
action between product type and the dispersion of review ratings on deci-
sion-making uncertainty was significant ($\beta = -.48, t = -2.78, p < .01$). The
effect of decision-making uncertainty on product evaluation, while control-
ling for the main effects of product type and the dispersions of review ratings
and their interaction, also obtained significance ($\beta = -.32, t = -3.93, p < .01$).
Finally, the indirect effect of product type and the dispersion of review
ratings through decision-making uncertainty was significant (95 percent
confidence interval [CI]: .092, .677). Although the conditional indirect effect
was positive for the comic book app (95 percent CI: .030, .380), it was
negative for the voice translator app (95 percent CI: -.399, -.010).

Discussion

Experiment 3 replicates the previous findings and further reveals that partici-
pants exposed to hedonic products felt lower levels of uncertainty when
making their own decisions after reading high versus low dispersions of
ratings compared to those exposed to utilitarian products. Mediation ana-
lyses showed that this reduced uncertainty led to more favorable product
evaluations with highly dispersed ratings for hedonic than for utilitarian
products (H3). This experiment also provided an experimental setting that
emulated a real-world online shopping environment. Not only were partici-
pants given access to simulated mobile app stores, they were also given more
natural peer ratings of a greater volume and with less extreme dispersions.
In this respect, Experiment 3 offers a deeper understanding of the findings
observed and permits greater generalizability of such findings using a more
ecologically valid methodology.

General Discussion and Implications

Theoretical Implications

The present research demonstrates that product evaluations improve for
hedonic products when the evaluators read high rather than low disper-
sions of ratings and that this interaction grows more pronounced at high
rather than low average ratings (Experiment 2). More important, the find-
ings replicated in a simulated mobile setting confirm the mediating role of
decision-making uncertainty, shedding light on the mechanism underlying
the observed interaction between product type and the dispersion of review
ratings (Experiment 3). Overall, these findings are particularly noteworthy
in terms of the refinements they offer to existing reference-dependent
models. Unlike models that predict that people prefer lowly dispersed
ratings at high average ratings [29, 31, 56, 61], this study demonstrates
that highly dispersed ratings prompt better evaluations for hedonic
products than lowly dispersed ratings, with such a tendency becoming
more pronounced at higher average ratings (Experiment 2). Nonetheless,
the findings still align with the extant model in that the relative merit of less risky options increases with high rather than low average ratings. The key difference of this study lies in the fact that the notion of risk is recast in terms of the ratings’ diagnosticity for decision outcomes. The reversal of risky options for hedonic goals is thus accounted for by the greater diagnosticity of highly dispersed ratings to predict whether a product fits the focal goals well. In this regard, this study offers a new, previously unexplored insight, namely that the nature of decision making that consumers face can determine the meaning of risk.

Furthermore, this research helps resolve the mixed findings about the effect of the dispersion of review ratings by focusing on the notion of preference heterogeneity, which constitutes a key difference between hedonic and utilitarian products. The empirical contrast of hedonic and utilitarian products within the same category (Experiments 2 and 3) parses out the proposed effect, without any potential contamination by uncontrolled, extraneous variables [45]. Consideration of the set of relevant confounding variables, including involvement and subjective knowledge, further reduces such concerns (Experiments 1–3). Moreover, the replicated study in an app store setting enhances the generalizability of these observations (Experiment 3). The mobile platform provides a more ecologically valid scenario, in which people casually search through their mobile devices for product- or service-related information [32]. Thus, the methodological approach strengthens the validity and robustness of the results.

Added to these contributions is the elucidation of the underlying mechanism behind the interaction between product type and the dispersion of review ratings (Experiment 3). By illuminating the role of decision-making uncertainty, this study confirms, albeit indirectly, that preference heterogeneity drives the relative merit of high dispersions of ratings for hedonic products [12, 17, 22, 48]. Implied in these findings is that consumers vary their decision-making uncertainty according to their perceptions of how accurately they can predict decision outcomes in terms of achieving their decision goals and that they use the dispersion of review ratings as the basis of such perceptions. Such differential perceptions of uncertainty fundamentally seem to be a result of the difference in preference heterogeneity that exists between hedonic and utilitarian products.

This information-diagnosticity approach to preference heterogeneity also adds to the understanding of the decreased negativity effects for hedonic products [43, 51]. The research has thus far explained that for hedonic products, the possibility of subjectivity in product reviews facilitates causal attribution to the reviewers (versus the product) and thereby prompts readiness to refute negative reviews. However, there still remains the question of why this readiness to refute reviews for subjectivity occurs only in negative rather than in positive reviews. Why is it easier to refute negative than positive reviews?

According to the information-diagnosticity framework, the positivity effect arises for hedonic products because the perception of multiple ideal points bolsters the information diagnosticity of positive ratings against negative ratings [17, 19, 20, 21]. What is noteworthy is that positive ratings
possess greater diagnosticity to resist being discounted in evaluations than their negative counterparts. Thus, because negative ratings are more vulnerable to being discounted than are positive ratings, consumers may more readily refute such negative ratings when they pursue hedonic goals. In this vein, the present research is not only in line with previous studies about causal attributions but also enriches their theoretical foundations by explicitly addressing the asymmetry in readiness to refute negative versus positive reviews via the notion of information diagnosticity.

**Managerial Implications**

The present research provides important managerial implications. The results show that highly dispersed ratings appeal more favorably to consumers of hedonic products. By facilitating the perception that more accurate predictions of decision outcomes are possible, highly dispersed ratings may attenuate the perceived uncertainty in decision making. Marketers thus need to ensure that consumers can easily recognize the dispersion of ratings, especially when it reaches high values; methods of doing this can include displaying bar graphs saliently, as done by epinion.com or by listing the best positive and negative reviews near the top of the Web pages as in buzzillions.com. This explicit highlighting of controversy indeed may produce more interest in the focal product and thereby generate more word of mouth [11, 39, 56]. Dan Brown’s *The Da Vinci Code*, for instance, sparked public interest at an early stage by publicizing the controversy over its sacrilegious theme [7].

However, this beneficial effect of controversy may not hold for utilitarian products, as consumers expect these products to meet convergent needs. For instance, Microsoft’s *Windows Vista* software encountered considerable controversy at its launch (reviews.cnet.com), eventually being neglected by most users for its failure to meet broadly accepted criteria—such as high compatibility with other software programs [58]. The controversy arising from not meeting more general needs might have adversely affected the evaluation of this utilitarian software.

**Limitations and Future Research**

First, this study employed completely or almost completely bipolar ratings formats to manipulate highly dispersed ratings. However, other dispersion variants exist, such as uniformly distributed ratings (i.e., the same number of votes for each of the five-star ratings). Prior experiments with coffee employed such a continuous range of dispersion, arguing that this manipulation seemed more realistic than extremely unanimous or bipolar ratings [8, 13]. Yet, consumers often make all-or-nothing decisions in reality, as exemplified by vast praise and simultaneous censure of avant-garde movies or new fashion styles (e.g., bikinis in the 1950s). People oscillate between the two poles of approval and objection; fierce verbal battles on television often
affect viewers’ positions on a given issue. Thus, bipolar ratings may be a good approximation of the reality in which consumers must formulate their own opinions on the basis of two extreme options. This criticism was mitigated in this paper by allowing some degree of deviations from purely bipolar ratings during Experiment 3 (Appendix C).

Second, although this study mainly focuses on investigating the effect of consumers’ numerical ratings, the identification of the origin of controversy for highly dispersed ratings through text analyses can offer a deeper understanding of consumers’ review reading behavior. Controversy often arises because reviewers differ either in the aspects of products they focus on or in the values they assign to these aspects [6]. Perhaps some movies arouse controversies because some reviewers focus more on inappropriate casting choices whereas others attend more to a well-structured plot. In another case, some movies may arouse such controversies because a plot twist seems rather arbitrary for some reviewers but seems quite surprisingly brilliant for others. In this regard, an analysis of textual reviews as well as simple numerical ratings merits further investigation to illuminate the sources of controversy. Sentiment analysis, a language-processing task that uses a computational approach, could be a particularly useful tool for achieving this goal because it enables one to identify the viewpoint underlying a text span and to indicate which specific features of a product are evaluated positively or negatively [53]. Although such an endeavor is not the primary objective of the present study, future research using this sentiment analysis on real reviews could provide deeper insight into how controversies among reviewers drive consumers’ purchase behavior.

Third, although this study proposed and found that highly versus lowly dispersed review ratings were favorable to evaluations of hedonic products, it would be intriguing to investigate boundary conditions for the observed findings. One may argue that excessive manipulations of bipolar ratings could backfire when extremely low ratings are included. Such a conjecture may suggest that consumers assume that realistic ratings should have more or less dispersed ratings depending on preference heterogeneity. They may not accept dispersed ratings even for hedonic products when the ratings deviate from their assumptions. Therefore, the assumption on the degree of preference heterogeneity deserves further investigation to elucidate the dynamics of the evaluation of dispersed ratings.

**Conclusion**

This research began with an attempt to examine a counterintuitive idea—that under some conditions, consumers prefer high over low dispersions of ratings. Three experiments reveal that high dispersions of ratings benefit hedonic products and their evaluations, because they reduce the perceived uncertainty of how accurately one can predict decision outcomes in terms of achieving the decision goals. This effect becomes particularly pronounced when average ratings are high rather than low, as predicted by the proposition that the pursuit of hedonic goals reverses general preferences for low
over high dispersions of ratings at high average levels. The replication study, performed on simulated mobile platforms, also adds to the growing literature that seeks to capture a real-world picture of online consumer behavior. Overall, marketers cannot simply ask whether high or low dispersions of ratings are good or bad; rather, they must consider their products to which each type of the review ratings points.

NOTES

1. One missing value was imputed by the EM (expectation-maximization) algorithm run over the entire data set, instead of being removed using casewise deletion.
2. One missing value was imputed by the EM algorithm run over the entire data set, instead of being removed using casewise deletion, as in Experiment 1.

REFERENCES


## Appendix A: Measurements of Confounding and Ancillary Variables

<table>
<thead>
<tr>
<th>Construct</th>
<th>Scale items</th>
<th>Studies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Involvement [38]</td>
<td>I have a strong interest in _____.</td>
<td>Pretest, Experiments 2 and 3</td>
</tr>
<tr>
<td></td>
<td>For me, _____ does not matter. (reverse coded)</td>
<td>Pretest, Experiments 2 and 3</td>
</tr>
<tr>
<td></td>
<td>_____ is very important to me.</td>
<td></td>
</tr>
<tr>
<td>Subjective knowledge [18]</td>
<td>I know pretty much about _____.</td>
<td>Pretest, Experiments 2 and 3</td>
</tr>
<tr>
<td></td>
<td>Compared to most other people, I know less about _____. (reverse coded)</td>
<td>Pretest, Experiments 2 and 3</td>
</tr>
<tr>
<td></td>
<td>I feel very knowledgeable about _____.</td>
<td>Pretest, Experiments 2 and 3</td>
</tr>
<tr>
<td></td>
<td>Among my circle of friends, I’m one of the “experts” on ____.</td>
<td></td>
</tr>
<tr>
<td>Prior category attitude [4]</td>
<td>_____ is favorable/unfavorable.</td>
<td>Pretest, Experiments 2 and 3</td>
</tr>
<tr>
<td></td>
<td>_____ is likable/dislikable.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>_____ is good/bad. (9-point scale)</td>
<td></td>
</tr>
<tr>
<td>Product familiarity [9]</td>
<td>The above _____ is new to me. (reverse coded; 1 = “strongly disagree,” 9 = “strongly agree”)</td>
<td>Experiments 2 and 3</td>
</tr>
<tr>
<td>Regulatory focus [10, 65]</td>
<td>How much satisfaction would you feel if your evaluation on the above book proves appropriate? (promotion focus; 1 = “no satisfaction at all,” 9 = “a lot of satisfaction”)</td>
<td>Experiments 2 and 3</td>
</tr>
<tr>
<td></td>
<td>How much regret would you feel if your evaluation on the above book proves inappropriate? (prevention focus; 1 = “no regret at all,” 9 = “a lot of regret”)</td>
<td></td>
</tr>
<tr>
<td>Online shopping experience [55]</td>
<td>Prior to your participation in this study, how would you rate your level of experience in terms of (1) going online; or (2) online browsing/shopping? (1 = “not experienced at all,” 9 = “very much experienced”)</td>
<td>Experiments 2 and 3</td>
</tr>
<tr>
<td>Possession of a driver’s license</td>
<td>Did you obtain a driver’s license? (yes or no)</td>
<td>Experiment 2</td>
</tr>
<tr>
<td>Type of smartphone used</td>
<td>What smartphone do you use? (1 = iPhone, 2 = Android, 3 = Blackberry, 4 = Windows, 5 = Nokia Symbian, or 6 = other)</td>
<td>Experiment 3</td>
</tr>
<tr>
<td>Smartphone usage period</td>
<td>How long have you used a smartphone? (1 = less than 1 month, 2 = 1-3 months, 3 = 2-6 months, 4 = 6 months-1 year, 5 = 1-1.5 years, 6 = 1.5-2 years, 7 = 2-3 years, 8 = 3-4 years, or 9 = more than 4 years)</td>
<td>Experiment 3</td>
</tr>
<tr>
<td>Smartphone usage frequency [35]</td>
<td>Approximately how often do you use a smartphone? (1 = “very infrequently” to 9 = “very frequently”)</td>
<td>Experiment 3</td>
</tr>
</tbody>
</table>

Note: All scales were anchored by 1 (“not at all”) and 9 (“very much so”), unless specified otherwise.
Appendix B: Sample Stimuli Materials for Experiments

A. Experiments 1 and 2

B. Experiment 3
Appendix C: Manipulation of the Dispersion of Review Ratings

<table>
<thead>
<tr>
<th>Average rating</th>
<th>Lowly dispersed ratings (Unanimous ratings)</th>
<th>Highly dispersed ratings (Bipolar ratings)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Two star (Experiment 2)</td>
<td><img src="chart1.png" alt="Two star chart" /></td>
<td><img src="chart2.png" alt="Two star chart" /></td>
</tr>
<tr>
<td>Three star (Experiments 1 and 2)</td>
<td><img src="chart3.png" alt="Three star chart" /></td>
<td><img src="chart4.png" alt="Three star chart" /></td>
</tr>
<tr>
<td>(Experiment 3)</td>
<td><img src="chart5.png" alt="Three star chart" /></td>
<td><img src="chart6.png" alt="Three star chart" /></td>
</tr>
<tr>
<td>Four star (Experiment 2)</td>
<td><img src="chart7.png" alt="Four star chart" /></td>
<td><img src="chart8.png" alt="Four star chart" /></td>
</tr>
</tbody>
</table>
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