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# Does Amazon Scare Off Customers? The Effect of Negative Spotlight Reviews on Purchase Intention

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**Abstract.** Online retailers provide review systems to consumers in order to improve perceived trustworthiness and boost sales. We examine the effects of review valence and valence intensity on consumer purchase intention. Review adoption emerges as a novel, important moderating variable. We find that positive reviews have a stronger effect on consumer purchase intention than negative reviews. Moderate reviews always lead to higher purchase intention than extreme reviews, but the size of the effect is greater for extremely negative reviews than moderately negative reviews. The effect is reversed for positive reviews. Our results imply that a recent innovation in Amazon's review system, highlighting negative reviews along with positive spotlight reviews, must be designed carefully to avoid losing customers. Choosing the wrong combination of reviews can diminish the positive effect of spotlight reviews on sales by nearly 20%.

**Keywords:** E-Commerce, Purchase Intention, Consumer Review System, Design

## 1 Introduction

Online retailing figures are predicted to continue growing over the next years [1]. This will lead to increased competition among online retailers to attract consumer spending. Recent research indicates that online consumers are particularly attracted by vendors whom they perceive to be highly trustworthy, who offer websites with a high level of usability [2], and who make online shopping feel more sociable [3]. These factors drive consumers' intention to use a vendor's website and purchase products from this website [4].

The decision to purchase a particular product also depends on other factors. Consumers will not buy a product if they are uncertain whether it matches their preferences or whether its quality is as good as advertised [5]. But evaluating products first-hand is costly. Among the possible sources of second-hand information, consumers are more likely to rely on other users than on seller-generated information [6] or even

third-party experts [7]. Retailers (e.g. Amazon, Walmart) thus introduced an imperfect but freely accessible substitute for first-hand product usage experience: consumer-generated reviews. Consumer review systems have indeed become extremely popular, and have been found to affect the sales of a variety of products [8-10].

The growing popularity of consumer review systems has, however, raised new issues. Consumers need to navigate increasingly large numbers of reviews to find those that are most relevant (or “helpful”) for product evaluation. Website designers are challenged to improve review system usability. In this context, one important feature is the “spotlight review” (e.g. Amazon). The most helpful positive review is displayed prominently near the top of each product’s review page (Fig. 1). Spotlight reviews reduce search and evaluation costs within the review system, since consumers are automatically presented with the review most likely to be of use for product evaluation. Results by [11] show that the impact of (positive) Amazon spotlight reviews on sales rank is indeed larger than the impact of other reviews. Recently, Amazon added the most helpful negative review for the product and now shows these two reviews side-by-side to prospective buyers.

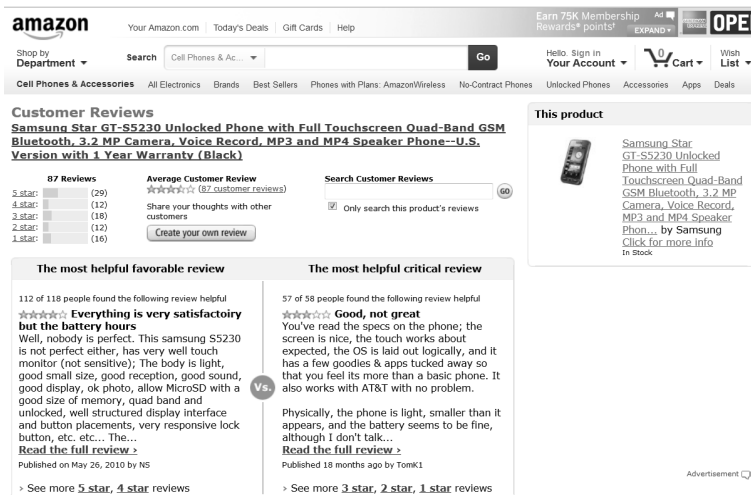


Fig. 1. Amazon spotlight reviews

Although presenting mixed spotlight reviews might be a good idea in the long term with a view to improving the review system’s perceived neutrality and trustworthiness, it might also have rather unpleasant effects (at least in the short term) on sales. If highlighting positive reviews increases sales, highlighting negative reviews may lead to a corresponding decrease in sales. The drop in sales could be even larger than expected, since consumers are known to rely more heavily on negative reviews than on positive reviews [12-14].

Whether reviews lead to a noticeable change in consumer (purchasing) behavior also depends on the propensity of readers to include information proffered in a review into their purchasing decision, which we refer to as “review adoption”. Our study is,

to the best of our knowledge, the first to measure the moderating effect of review adoption on purchase intention. We find that review adoption indeed plays a crucial role. We also explain why certain combinations of positive and negative reviews have a less negative effect on purchase intention than others and present an optimal configuration for mixed spotlight reviews.

The remainder of the paper is organized as follows. In section 2, we summarize previous research on the effect of review valence and valence intensity on purchase intention, and the moderating effect of review adoption. Section 3 describes our treatments, the experimental set-up and our sample. In section 4, we present the results of our data analysis. Finally, we discuss the findings and limitations of our study in section 5.

## 2 Theoretical Foundations and Research Model

Previous research indicates that review valence and valence intensity are the most salient review features for explaining sales success (e.g. [9], [15-16]). Review valence refers to positive or negative evaluation of a product or service [17]. Valence intensity describes the strength with which the opinion is voiced in the review [18]. Both valence and valence intensity determine review diagnosticity [19]. Highly diagnostic reviews make it easy for readers to assign the reviewed product to precisely one cognitive category, for instance “bad quality” [20]. They reduce product uncertainty by a greater degree than reviews with low levels of diagnosticity. Hence, readers are more likely to include a review with a high level of diagnosticity into their decision-making process. To account for the fact that some readers are generally more likely than others to adopt third-party opinions [21], we introduce a moderating variable in subsection 2.3. Previous research on the effects of valence and valence intensity on purchase intention is discussed in the following two subsections.

### 2.1 Valence of Online Consumer Reviews

Ghose and Ipeiritis noted that the average customer rating had a significant effect on the sales rank of audio and video players [9]. The average rating also influenced digital cameras’ sales ranks [22] and books’ sales ranks on Amazon [8],[11],[23]. Several studies on the effect of valence on purchase intention found that negative reviews had a greater influence on purchase intention or sales than positive reviews [12],[24-25].

Herr et al. showed that highly diagnostic product information is significantly more likely to be recalled than low-level diagnostic information, especially if the former is negative [14]. This finding is explained by the *brilliant-but-cruel* hypothesis, or *negativity bias*, which states that negative evaluators are assumed to be more intelligent and perceptive and their opinions are therefore accorded greater importance than positive ones [13].

Another reason why online consumers may be more inclined to believe negative reviews is put forward by [8]: consumers may expect a higher percentage of positive review to be fraudulent than of negative reviews. If consumers perceive such a “ma-

nipulation bias” in positive reviews, these reviews are no longer useful for reducing product uncertainty [26].

If prospective customers view the purchase from a gains perspective and try to minimize the risk involved in the purchase [27], they may also be more likely to be influenced by negative reviews than positive reviews.

**H1:** Negative product reviews have a stronger effect on consumer purchase intention than positive product reviews.

## 2.2 Valence Intensity of Online Consumer Reviews

Extreme reviews exhibit a high level of diagnosticity: they permit the consumer to classify the reviewed product almost instantly as “good” or “bad”. Indicators for high valence intensity (extremity) are, for instance, excessive use of exclamation marks, use of emotionally charged words (“fantastic”, “horrifying”), and the intensity of different parts of speech, like adverbs (“hugely”, “superbly”) [18],[28].

Assigning category membership on the basis of moderate reviews demands a greater cognitive effort from the reader, which ought to lead to a smaller reduction in product uncertainty and lower persuasiveness. Another reason why consumers may be more likely to rely on extreme reviews rather than moderate reviews is the initial attitude towards a product. Reviews with moderate valence intensity have less impact on consumers’ evaluations when their prior preferences or their commitment to product choice are neutral or negative, i.e. if initially they do not have strong interest in buying this product [29].

Pavlou and Dimoka showed that extremely negative reviews for eBay sellers had a greater impact on price premiums than extremely positive or moderate reviews [30]. Forman et al. and Ghose and Ipeirotis found that moderate online consumer reviews were considered less helpful than strong negative or positive reviews [9],[31]. Results by [19] showed that, for utilitarian goods, extreme online consumer reviews were more helpful than moderate reviews, although for experiential goods they found the opposite effect.

Previous research also examined the relationship between valence intensity and purchase intention. Extremely negative book reviews were found to have a greater effect on consumer purchase intention than extremely positive reviews, indicating that (extremely) negative recommendations draw more attention than strong positive recommendations [32-33].

**H2:** Extreme reviews will have a greater effect on buying intentions than moderate reviews.

## 2.3 The Moderating Effect of Review Adoption

Online reviews are a means of virtual knowledge transfer in the sense that consumers learn about (perceived) product quality from other consumers’ opinions and experiences. How much they learn depends on how willing they are to adopt other consumers’ opinions. Attribution theory suggests that readers of (largely anonymous) reviews

try to infer from review content to which extent their preferences overlap with the reviewer’s preferences [34].

Other determinants of review adoption, apart from review-related features like the reviewer’s preferences, are the reader’s personal characteristics. For one, individual product-related preferences dictate whether a particular review is suitable for adoption. Second, some readers are generally more likely to adopt other people’s opinions than others (e.g. [21]). Bailey found that consumers who are more susceptible to third-party influence perceived review websites to be more important for the purchasing process [35]. Recent research showed that this tendency influenced the intention of travelers to follow advice obtained in a travel community [36].

This suggests that review adoption moderates the effect of review valence and valence intensity on consumer purchase intention.

**H3a:** The effect of review valence on purchase intention will increase if review adoption is high.

**H3b:** The effect of review valence intensity on purchase intention will increase if review adoption is high.

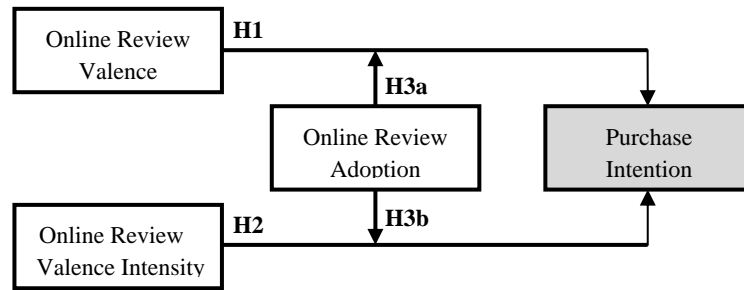


Fig. 2: Research model

### 3 Research Methodology

#### 3.1 Treatments

We conducted a between-subject laboratory experiment with 170 participants to test our hypotheses. Based on valence and valence intensity, we designed four treatments and chose four reviews accordingly: moderately positive (MP), extremely positive (EP), moderately negative (MN) and extremely negative (EN). Each participant was randomly assigned to one of these treatments.

For each treatment, we selected a review which fitted treatment valence and valence intensity. In a first step, we manually selected 10 reviews from Amazon.com. Valence was determined on the basis of the overall “star” rating (5 or 4 stars for “positive” and 1 or 2 stars for “negative”). Valence intensity was determined based on the usage of intense language in the review (see subsection 2.2 for examples).

In the second step, we carried out a pretest with 24 participants who evaluated these 10 reviews with regard to their valence and valence intensity. We then chose the 4 reviews that fitted our experimental conditions best.

The object of all selected reviews is the smartphone “Samsung Star 5230”. We decided to use this product because i) our sample (young with academic background) was likely to be familiar with the product category, ii) it has attracted a sufficient number of reviews for our purposes and iii) it has attracted both positive and negative as well as moderate and extreme reviews.

We controlled for a number of factors that might influence reader reactions to a review. First, we made sure that the reviews focussed on the same product features, and that the features could be assumed to be reasonably relevant to most smartphone buyers. We selected reviews discussing screen, battery time, widgets, camera resolution and internet capabilities. Second, we chose reviews of approximately the same length: each review consisted of 246-270 words. Moderate reviews were characterized by significantly less personal and possessive pronouns (PM=1.9%, NM=1.5%) and exclamation marks (PE=20, NE=16) than extreme reviews (pronouns: PE=4.9%, NE=5.2%; exclamation marks: PM=2, NM=2).

### 3.2 Experimental Procedure

The participants first read a brief description of the smartphone. In order to avoid introducing design or brand bias, we anonymized the description and showed no pictures to the participants. Each participant was then asked to reveal her initial purchase intention for the smartphone. Next, the participants were shown the treatments (i.e. the reviews) and asked to read them carefully. We then asked the participants to state their propensity to adopt the review and, again, their purchase intention. Finally, we inquired about their opinions on review valence and valence intensity to check whether they had interpreted the treatment correctly.

The dependent variable, purchase intention, was measured with a single item on a seven-point-scale from “-3”, extremely unlikely, to “3”, extremely likely. The moderating variable, review adoption, was measured on a seven-point scale with the following four items (Table 1). The scale is highly reliable (Cronbach’s  $\alpha=0.89$ ).

We measured the participants’ perceptions of review valence and valence intensity on two seven-point semantic differential scales (valence: -3=“negative”, 3=“positive”; valence intensity: -3=“extreme”, 3=“moderate”).

**Table 1.** Items for review adoption

Item	Adapted from
1	The review will crucially affect my decision to purchase or not to purchase the smartphone. Jeon & Park (2003)
2	I will refer to this review in my purchase decision. Jeon & Park (2003)
3	The review will make it easier for me to decide whether to purchase or not to purchase the smartphone. Cheung et al. (2009)
4	I will rely on the review to make a purchase decision. Cheung et al. (2009)

### 3.3 Sample

Participants were nearly evenly distributed across the four treatment conditions (see Table 2). The participants were between 20 and 40 years of age; 65% were female. A total of 78% were students whilst 18% were currently employed. More than half the participants (61%) used a smartphone in everyday life. Although they frequently consulted online consumer reviews to make purchase decisions, they did not write reviews themselves. One-way ANOVA tests revealed no differences for either the demographic or the review-related variables.

**Table 2.** Descriptive statistics of our sample

	<b>Extremely positive</b>	<b>Moderately positive</b>	<b>Extremely negative</b>	<b>Moderately negative</b>	<b>F</b>	<b>Sig.</b>
Sample size	43	45	40	42	-	-
Reading reviews*	3.21 (0.833)	3.18 (0.614)	3.33 (0.694)	3.36 (0.656)	0.658	0.579
Writing reviews*	1.47 (0.667)	1.60 (0.720)	1.48 (0.679)	1.52 (0.740)	0.336	0.799

\* (from 1=“never” to 4=“very often”)

## 4 Data Analysis and Results

### 4.1 Data Analysis

We first conducted manipulation checks to examine whether the participants had interpreted the reviews’ valence and valence intensity as we had intended. One-way ANOVA tests showed that the manipulation was successful (MEP=6.5, MMP=5.6, MEN=1.2; MMN=2.2, F=486.628, p<0.001).

Since our dependent variable is measured on an ordinal scale, we chose ordered logit regression for testing our hypotheses.

We measured the effects of valence and valence intensity on purchase intention with two dummy variables. The first dummy variable accounts for review valence, -1 symbolizing negative and +1 positive reviews. The second dummy variable contrasts reviews with extreme (-1) and moderate (+1) valence intensity. Review adoption was measured on a seven-point scale. We standardized all independent variables to make their estimates comparable. Our model, including all interaction effects, is summarized by the following equation.

*PurchaseIntention*

$$\begin{aligned}
 &= \alpha + \beta_1 \text{Valence} + \beta_2 \text{ValenceIntensity} + \beta_3 \text{ReviewAdoption} \\
 &+ \beta_4 \text{Valence} \times \text{ValenceIntensity} + \beta_5 \text{ReviewAdoption} \\
 &\times \text{Valence} + \beta_6 \text{ReviewAdoption} \times \text{ValenceIntensity} \\
 &+ \beta_7 \text{ReviewAdoption} \times \text{Valence} \times \text{ValenceIntensity} + \varepsilon
 \end{aligned} \tag{1}$$



## 4.2 Results

Our regression analysis indicates an outstanding fit with a highly significant likelihood ratio ( $p < 0.001$ ) and Nagelkerke's R-square value of 0.483 (Table 3). Variance inflation factors of at most 1.06 indicate absence of multicollinearity. Valence has the strongest effect on purchase intention, followed by the interaction effect between review adoption and valence. The interaction between valence and valence intensity does not contribute to explaining purchase intention. Although it is nearly significant, the confidence interval reveals that the effect's direction cannot be ascertained.

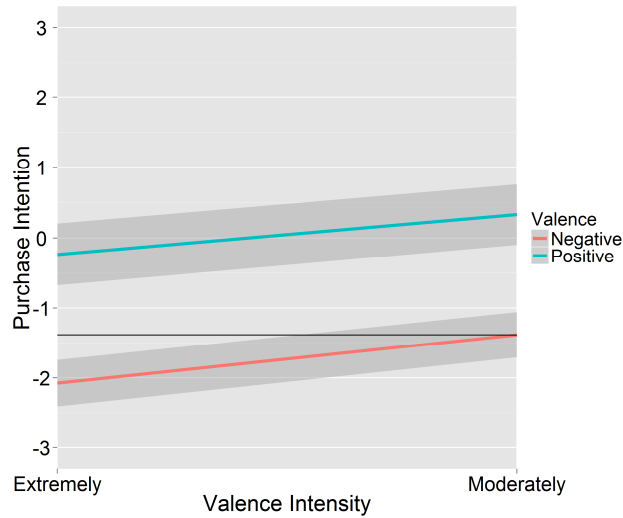
**Table 3.** Results of ordered logit regression analysis

Independent Variable	Estimate	Std. Err.	Conf. Interval		Sig.
			2.5%	97.5%	
Valence	1.478	0.180	1.135	1.840	<0.001
Valence Intensity	0.390	0.146	0.105	0.679	0.008
Valence x Valence Intensity	-0.240	0.146	-0.527	0.046	0.103
Review Adoption	0.204	0.157	-0.101	0.515	0.194
Review Adoption x Valence	0.829	0.161	0.517	1.149	<0.001
Review Adoption x Valence Intensity	0.152	0.150	-0.140	0.451	0.311
Review Adoption x Valence x Valence Intensity	-0.095	0.151	-0.393	0.199	0.530
Log-Likelihood	-248.055***				
Nagelkerke's R <sup>2</sup>	0.483				

The positive estimate for valence indicates that positive reviews have a greater influence on purchase intention than negative reviews. We also found that moderate reviews have a stronger effect on purchase intention than extreme reviews.

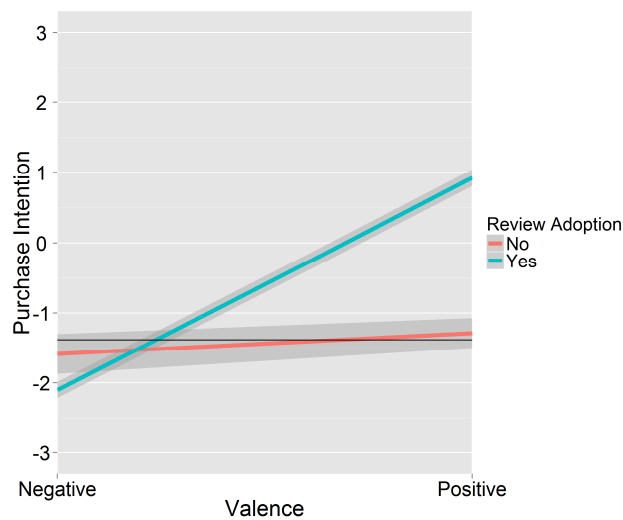
Before we can continue to interpret our regression results, we need to put them into relation with the participants' initial purchase intention, which we measured prior to the treatments. Initial purchase intention was slightly negative, with an average value of -1.38 (SD=1.40). Figure 3 shows that positive reviews lead to a greater change of the initial purchase intention (indicated by the black horizontal line) than negative reviews. Hypothesis 1 is not supported.

An interesting finding illustrated in Figure 3 is the fact that moderately negative reviews have virtually no effect on purchase intention. In contrast, extremely negative reviews significantly decrease the intention to purchase. Positive reviews significantly change purchase intention regardless of valence intensity. The effect is greater, however, for moderately positive reviews. Hence, hypothesis 2 is supported for negative reviews only.



**Fig. 3.** Impact of review valence and valence intensity on purchase intention

In H3a, we suggested that the relationship between review valence and purchase intention is moderated by review adoption. Our regression results strongly support this hypothesis. Figure 4 shows the interaction effect of valence and review adoption on purchase intention along with our participants' initial purchase intention. Our results support the intuition that reviews only affect purchase intention if adopted by the consumer. Among the adopted reviews, positive reviews have a stronger effect on purchase intention.



**Fig. 4.** Relationship between review valence and review adoption

The effect of valence intensity is not moderated by review adoption (Table 3). Hypothesis 3b must be rejected. So far, our results appear to indicate that highlighting a negative review alongside a positive review will not have a negative short-term effect on sales. However, this holds true only if a greater number of consumers adopt the positive review. The overall effect on sales could become negative if the number of consumers who adopt the negative review is greater.

When we compared how many of our participants had adopted the positive and negative reviews, we actually found that negative reviews ( $p=0.013$ ) and moderate reviews ( $p=0.001$ ) are adopted more often.

These results suggest an interesting trade-off. On the one hand, positive reviews are more influential than negative reviews, but on the other hand negative reviews are adopted more often. This lends further support to the negativity bias reported in previous studies.

The total effect of mixed “spotlight reviews” on purchase intention is unclear. It depends both on valence and valence intensity and on the propensity of consumers to adopt the presented reviews. We therefore decided to examine the total effect of mixed “spotlight reviews” in a simulation.

### 4.3 Economic Effect of Spotlight Reviews

We simulated 50,000 consumers presented with one negative and one positive review. Simulations were based on the initial purchase intention  $PI_{initial}$ , the review adoption decision (RA) and the final purchase intention (PI) in our experimental data. The following equation gives the total effect after both reviews have been read:

$$Effect = \frac{PI^+ \cdot RA^+ + PI^- \cdot RA^-}{2} - PI_{initial} \quad (2)$$

A positive total effect indicates that the positive review has more influence than the negative review and, in other words, sales (rank) improve. We decomposed the total effect into its positive, negative and neutral fractions to improve the interpretability of our simulation.

We estimated the proportions of all three effects for positive and negative reviews with moderate and extreme intensity respectively. In addition, we pooled all positive and negative reviews regardless of intensity to compute the effects of randomly selected moderate and extreme reviews. Table 4 summarizes our simulation results.

**Table 4.** Simulation results on the economic effect of “spotlight reviews”

	Positive effect	Neutral effect	Negative effect
Mod. pos. vs. mod. neg.	89.38 %	7.97 %	2.65 %
Mod. pos. vs. ext. neg.	84.94 %	6.08 %	8.98 %
Ext. pos. vs. mod. neg.	78.14 %	15.70 %	6.16 %
Ext. pos. vs. ext. neg.	67.27 %	12.61 %	20.12 %
Pos. vs. neg.	80.13 %	10.41 %	9.46 %

Our results indicate that the combination of a moderately positive review and a moderately negative review is superior to all others. It displays the highest proportion of positively affected consumers and the lowest proportion of negatively affected consumers.

Although our experimental results showed that extremely positive reviews have a strong impact on purchase intention, we must advise against highlighting extremely positive reviews. Our simulation results reveal that extremely positive reviews are much less often adopted than moderately positive reviews. Extremely negative reviews have a noticeably stronger effect than moderately negative reviews – in particular when combined with extremely positive reviews. We advise strongly against using such a combination.

## **5 Discussion**

In this paper, we examine the influence of valence, valence intensity and review adoption on purchase intention and find a strong effect for all variables. In contrast to recent literature, our results indicate that positive reviews have a greater impact on consumers' purchase intentions than negative reviews. Although moderate reviews lead to a higher purchase intention than extreme reviews, the size of the effect is greater for extremely negative reviews than moderately negative reviews. The reverse is true for positive reviews. As expected, review adoption is an important moderating variable. Only adopted reviews have an impact on purchase intention at all, and adopted positive reviews are more influential than adopted negative reviews. We also find that consumers are more likely to adopt negative rather than positive reviews, and moderate rather than negative reviews. Our simulation results indicate that the total effect of presenting both negative and positive "spotlight reviews" is always positive, but that there is a noticeable difference between the best combination (both reviews are moderate) and the worst combination (both reviews are extreme). The positive effect is reduced by over 22%, and the negative effect increases by nearly 18%. These results contain interesting implications for both practitioners and researchers.

Online retailers such as Amazon encourage their customers to share their opinions about products. Customer reviews have emerged as an important sales driver. The major challenge for retailers now consists in balancing their review systems to meet very diverse demands. The review system's perceived trustworthiness and neutrality must be protected, it being the antecedent for all gains to be realized from consumer opinion sharing. Second, review system usability must be sufficiently good for keeping consumer search and evaluation costs at a reasonable level. Third, the review system must have an overall positive effect on sales to justify expenses incurred and, indeed, its very existence to both retailer and product manufacturers.

In this context, the case of mixed "spotlight reviews" is particularly interesting. On the one hand, highlighting a negative review decreases purchase intention. On the other hand, it most likely increases perceived neutrality and trustworthiness of the entire review system. Having examined the effect on purchase intention, we conclude that presenting mixed "spotlight reviews" is not detrimental to sales in any scenario. However, we would advise online retailers to present moderate rather than extreme

reviews if they wish to maximize purchase intention. Although consumers are more likely to adopt moderate negative reviews, they have hardly any effect on purchase intention. Extremely positive reviews do have a higher impact on purchase intention than moderately positive reviews, but consumers are so unlikely to adopt extremely positive reviews that the total effect is actually smaller.

Amazon chooses “spotlight reviews” based on their helpfulness scores. Since it has not been ascertained yet whether the most helpful reviews are also the ones that are most likely to be adopted (results by [9] indicate that this might not be the case), an additional mechanism for discerning moderate and extreme reviews within the category “most helpful reviews” is required. One possible solution is tagging a small set of reviews manually and then training a support vector machine to classify these reviews into extreme and moderate ones. This, of course, is assuming that there exist a number of reviews with comparably high helpfulness scores such that consumers are indifferent which one is presented as the “spotlight review”.

For future research, it is vital that the relationship between review adoption and helpfulness be examined. Intuitively, one might suppose helpfulness to be an indicator for review adoption. However, there is little evidence why consumers vote on some reviews but not on others [37]: one explanation that has been put forward is that consumers vote to express their (dis)agreement with the review opinion even if they are not deliberating the purchase of the reviewed product. No direct link between helpfulness and review adoption has been established so far. Moreover, there might even exist a voting bias. An analysis of six different product categories on Amazon shows that positive reviews have a largely higher absolute number of votes than negative reviews<sup>1</sup> – which is particularly surprising in view of the evidence in favor of the existence of a negativity bias in reviews. If consumers are generally more likely to vote for positive reviews, helpfulness cannot be used to measure review adoption.

This study presents, to the best of our knowledge, the first experiment on review adoption as a moderating variable in the relationships between valence and valence intensity and purchase intention. Most research in this area uses field data, which is subject to a number of potential biases. Recent research shows, for instance, that product descriptions reduce product uncertainty, but that this effect is moderated by the degree of vendor uncertainty [5]. Another issue is the fact that it is impossible to determine whether customers who bought an item actually read the reviews and, if so, whether the reviews were the decisive factor in their purchasing decision [19]. We decided to exclude all potential biases inherent in field data by setting up a laboratory experiment to examine the effect of valence, valence intensity and review adoption on purchase intention.

Our findings are still subject to two major limitations. First, we used only one product in our experiment. Recent studies revealed significant differences between

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<sup>1</sup> We found the difference in the number of positive and negative votes to be highly significant across both experiential and utilitarian product categories ( $p < 0.001$ ). We collected data for digital cameras (positive: 249085, negative: 71486), smartphones (positive: 351762, negative: 165086), notebooks (positive: 43879, negative: 12588), daypacks (positive: 2499, negative: 215), board games (positive: 70415, negative: 18961), eau de toilettes (positive: 29463, negative: 10182).

reviews on products of different type and/or category, and also between readers' perceptions of reviews on different product types and categories [9],[19]. Our experimental results are very likely not generalizable to other product types and categories. Second, review adoption may also depend on product type. Our study shows that negative reviews are adopted more frequently, but that the total effect of adopted positive reviews is larger than of adopted negative reviews. We used a smartphone, which is usually classified as utilitarian product [19],[38]. Sen and Lerman examined reviews of experiential products and found, contrary to our results, no evidence for a negativity bias [39]. They drew on attribution theory to explain this surprising result. Consumers attribute the negative opinion voiced in reviews of experiential products to the reviewers' preferences and attitudes, not to product quality. This leads to decreased trust in negative reviews of experiential reviews and explains the absence of a negativity bias. Research into the moderating effects of product types and categories on review adoption is necessary to improve our understanding of online consumer behavior and derive more general guidelines on how to design online review systems.

## References

1. Gill, M., Evans, P.F., Sehgal, V., Da Costa, M.: European Online Retail Forecast: 2011 To 2016. Online Retail Sales Growth In: Europe will Continue to Outpace Offline Growth For Years To Come. Forrester Research (2012)
2. Chen, Y.-H., Hsu, I.-C., Lin, C.C.: Website attributes that increase consumer purchase intention: A conjoint analysis. *Journal of Business Research*. 63, 1007–1014 (2010)
3. Kumar, N., Benbasat, I.: The Influence of Recommendations and Consumer Reviews on Evaluations of Websites. *Information Systems Research*. 17, 425–439 (2006)
4. Pavlou, P., Liang, H., Xue, Y.: Understanding and Mitigating Uncertainty in Online Exchange Relationships: A Principal-Agent Perspective. *Management Information Systems Quarterly*. 31 (2007)
5. Dimoka, A., Hong, Y., Pavlou, P.A.: On Product Uncertainty In Online Markets: Theory and Evidence. *MIS Quarterly*. 36, 395–426 (2012)
6. Bickart, B., Schindler, R.M.: Internet Forums As Influential Sources Of Consumer Information. *Journal of Interactive Marketing*. 15, 31–40 (2001)
7. Chen, Y., Xie, J.: Online Consumer Review: Word-of-Mouth as a New Element of Marketing Communication Mix. *Management Science*. 54, 477–491 (2008)
8. Chevalier, J.A., Mayzlin, D.: The Effect of Word of Mouth on Sales: Online Book Reviews. *Journal of Marketing Research*. 43, 345–354 (2006)
9. Ghose, A., Ipeirotis, P.G.: Estimating the Helpfulness and Economic Impact of Product Reviews: Mining Text and Reviewer Characteristics. *IEEE Transactions on Knowledge and Data Engineering*. 23, 1498–1512 (2011)
10. Ehrmann, T., Schmale, H.: The Hitchhiker's Guide to the Long Tail: The Influence of Online-Reviews and Product Recommendations on Book Sales - Evidence from German Online Retailing. *ICIS 2008 Proceedings* (2008)
11. Dhanasobhon, S., Chen, P.-Y., Smith, M., Chen, P.: An Analysis of the Differential Impact of Reviews and Reviewers at Amazon.com. *ICIS 2007 Proceedings* (2007)
12. Park, C., Lee, T.M.: Information direction, Website reputation and eWOM effect: A moderating role of product type. *Journal of Business Research*. 62, 61–67 (2009)

13. Amabile, T.M.: Brilliant but cruel: Perceptions of negative evaluators. *Journal of Experimental Social Psychology*. 19, 146–156 (1983)
14. Herr, Paul M, Kardes, Frank R, Kim, J.: Effects of word-of-mouth and product-attribute information on persuasion: An accessibility-diagnostics perspective. *Journal of Consumer Research*. 17, 454–462 (1991)
15. Chen, P.-Y., Wu, S., Yoon, J.: The Impact of Online Recommendations and Consumer Feedback on Sales. *ICIS 2004 Proceedings* (2004)
16. Cui, G., Lui, H., Guo, X.: Online Reviews as a Driver of New Product Sales. 2010 International Conference on Management of e-Commerce and e-Government. pp. 20–25. *IEEE* (2010)
17. Liu, Y.: Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue. *Journal of Marketing*. 70, 74–89 (2006)
18. Li, J., Zhan, L.: Online Persuasion: How the Written Word Drives WOM - Evidence from Consumer-Generated Product Reviews. *Journal of Advertising Research*. 51, 239 (2011)
19. Mudambi, S., Schuff, D.: What Makes a Helpful Online Review? A Study of Customer Reviews on Amazon.com. *Management Information Systems Quarterly*. 34, 185 – 200 (2010)
20. Feldman, J.M.L.J.: Self-Generated Validity and Other Effects of Measurement on Belief, Attitude, Intention and Behavior. *Journal of Applied Psychology*. 73, 421–435 (1988)
21. Bearden, W.O.N.: Measurement of Consumer Susceptibility to Interpersonal Influence. *Journal of Consumer Research*. 15, 473–481 (1989)
22. Jiang, B.-J., Wang, B.: Impact of Consumer Reviews and Ratings on Sales, Prices, and Profits: Theory and Evidence. *ICIS 2008 Proceedings Paper 85* (2008)
23. Sun, M.: How Does the Variance of Product Ratings Matter? *Management Science*. 58, 696–707 (2011)
24. Xia, L., Bechwati, N.N.: Word Of Mouse : The Role of Cognitive Personalization in Online Consumer Reviews. *Journal of Interactive Advertising*. 9, 3–13 (2010)
25. Doh, S.-J., Hwang, J.-S.: How consumers evaluate eWOM (electronic word-of-mouth) messages. *Cyberpsychology & behavior : the impact of the Internet, multimedia and virtual reality on behavior and society*. 12, 193–7 (2009)
26. Hu, N., Bose, I., Gao, Y., Liu, L.: Manipulation in digital word-of-mouth: A reality check for book reviews. *Decision Support Systems*. 50, 627–635 (2011)
27. Daniel Kahneman, Amos Tversky: Prospect Theory: An Analysis of Decision under Risk. *Econometrica*. 47, 263–292 (1979)
28. McEwen, W.J., Greenberg, B.S.: The Effects of Message Intensity on Receiver Evaluations of Source, Message and Topic. *Journal of Communication*. 20, 340–350 (1970)
29. Ahluwalia, R., Burnkrant, R.E., Unnava, H.R.: Consumer Response to Negative Publicity: The Moderating Role of Commitment. *Journal of Marketing*. 37, 203–214 (2000)
30. Pavlou, P.A., Dimoka, A.: The Nature and Role of Feedback Text Comments in Online Marketplaces: Implications for Trust Building, Price Premiums, and Seller Differentiation. *Information Systems Research*. 17, 392–414 (2006)
31. Forman, C., Ghose, A., Wiesenfeld, B.: Examining the Relationship between Reviews and Sales: The Role of Reviewer Identity Disclosure in Electronic Markets. *Information Systems Research*. 19, 291–313 (2008)
32. Godes, D., Mayzlin, D.: Using Online Conversations to Study Word-of-Mouth Communication. *Marketing Science*. 23, 545–560 (2004)
33. Floh, Arne, Koller, Monika, Zauner, A.: The Impact Of Perceived Valence, Perceived Information Credibility And Valence Intensity Of Online Reviews On Purchase Intentions.

- Proceedings of the Ninth International Conference on Electronic Business (ICEB), pp. 257–264. Macau (2009)
34. Folkes, V.S.: Recent attribution research in consumer behavior: A review and new directions. *Journal of Consumer Research*. 14, 548–565 (1988)
  35. Bailey, A.A.: Consumer Awareness and Use of Product Review Websites. *Journal of Interactive Advertising*. 6, 68–81 (2005)
  36. Casaló, L.V., Flavián, C., Guinalú, M.: Understanding the Intention to follow the Advice Obtained in an Online Travel Community. *Computers in Human Behavior*. 27, 622–633 (2011)
  37. Hao, Y., Li, Y., Zou, P.: Why some online product reviews have no usefulness rating? PACIS 2009 Proceedings (2009)
  38. Nelson, P.: Information and Consumer Behavior. *Journal of Political Economy*. 78, 311–329 (1970)
  39. Sen, S., Lerman, D.: Why are you telling me this? An examination into negative consumer reviews on the Web. *Journal of Interactive Marketing*. 21, 76–94 (2007)