Do Customer Reviews Drive Purchase Decisions? The Moderating Roles of Review Exposure and Price

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Abstract

Customers read reviews to reduce the risk associated with a purchase decision. While prior studies have focused on the valence and volume of reviews, this study provides a more comprehensive understanding of how reviews influence customers by considering two additional factors—exposure to reviews and price relative to other products in the category. Data provided by two online retailers are used for the analysis. The results reveal a four-way interaction with the effect of valence on purchase probability strongest when (1) there are many reviews, (2) the customer reads reviews, and (3) the product is higher priced. The effects of valence are smaller, but still positive, in the other conditions. We develop theoretical explanations for the effects based on dual processing models and prospect theory, and provide a sensitivity analysis. We discuss implications for academics, manufacturers and online retailers.

Keywords: Customer reviews, Elaboration likelihood model, Co-creation, Heuristic systematic model, Price, Reflective mind

1. Introduction

With the introduction of modern technologies such as the Internet, customers have become more active and empowered. Customers can now share opinions and experiences with services and products through online reviews and can do so in real time (i.e., while experiencing the product). Since information provided by other customers is often perceived as more interesting and trustworthy than information provided by the firm/brand [1], online customer reviews are believed to have a significant influence on customers' purchase decisions [2] and hence sales. As such, online reviews have been adopted by companies as an effective way to engage customers in product co-creation and influence those reading the reviews. These efforts have subsequently attracted much attention from academics across disciplines.

Although there has been abundant research on the influence of different review features such as valence, volume, helpfulness, and recency, the results from these studies are mixed overall [3, 2]. This is especially evident when we look at previous research studying the effect of a product's review valence on its sales [4]. Previous research has not shown a clear causal relationship between online product reviews and products' sales, but rather that this effect depends on the business context. In addition, previous research is limited to a number of specific product categories (e.g., books and movies) and data sources (e.g., Amazon) [5, 4]. Even though research investigating the effect of online reviews on sales has been rapidly growing, our understanding of the effects of online reviews is still blurred (see our discussion below) and scholars call for more research trying to reconcile the inconsistencies between previous studies [4].

A potential reason for these conflicting findings may be the limited number of product categories studied [5, 4]. Another explanation for the mixed results may be that extant research has not investigated interactions between features of online reviews [6]. It is also possible that the effects of online reviews differ based on the price of the product. However, there is no study yet that has examined the interactions of online review features with the price of the product. In addition, prior research has not devoted much attention to whether or not reviews were actually read. This is a serious limitation since previous studies assume that customers read reviews, or that customers read more helpful reviews [7].

Broadly speaking, online reviews can be characterized in terms of quantitative and qualitative features [8], and they can exert effects on customers in two ways—heuristically and systematically. Quantitative features (i.e., average star rating and number of reviews) are heuristic cues that a customer can observe without looking at the text of reviews, because these cues are often displayed next to the product description. Qualitative features require additional effort—a customer must either click on a 'review tab' or scroll down to be exposed to the reviews' text, which must be read and processed more systematically. By ignoring review exposure, existing literature disregards the first step of how reviews influence customers, namely the customer's decision to read the reviews [9]. Therefore, we do not know whether customers' purchase decisions are based only on heuristic cues or whether reading reviews plays a significant role in the decision making process. Ignoring the fact that exposure to reviews may play a significant role in customers' purchase decisions can lead to misspecification of empirical models and biased estimates for heuristic cues. Additionally, previous research, being mostly experimental [10], does not study the effects of reading reviews on actual purchase decisions. Rather, these studies focus on psychological outcomes such as attitudes, usefulness and intentions [11], or proxy measures such as sales rank [12, 13, 9].

To fill these gaps in the literature, we conduct an empirical analysis of data obtained from two online retailers to examine how the effect of review valence and volume on purchase decisions is moderated by the effects of review exposure and product price relative to the product category. We investigate how reading reviews (versus relying solely on numeric heuristic cues) and product price moderate the effect of review features on customers' purchase probability. In addition, we study dozens of categories from the consumer package goods industry and speciality-gift-product category. We build on dual-processing theories to explain how these factors interact with each other and influence customers' purchase probability.

2. Literature review and theoretical framework

2.1. Review valence and volume

Review valence is the average number of stars given to a product by customers who have previously reviewed the product. It informs consumers how previous customers have evaluated the product, and can be used to draw conclusions about the overall product quality [6].

Review volume is the number of reviews written about a product. It can signal the popularity of a product and the intensity of word of mouth [14, 15, 16, 17]. When potential customers observe that many other customers have reviewed the product, they may infer that these individuals have probably bought the product. Since individuals often learn by observing and imitating others [1, 18], this may lead to the bandwagon effect [5]. Also, higher volume can signal that more consumers care about the brand or product, and hence take the time to write a review about it [19]. The volume of reviews can also be indicative of consumers' enthusiasm for the product [17].

Research on the effects of valence and volume has yielded inconsistent results [4]. Some studies have found valence to have a positive effect on the sales rank of electronics [20], books and movie box office performance [13, 21, 22]. Other studies have found that valence has a direct effect on sales of cellphones [23], consumer package goods [24], and beer [25]. However, other studies have found valence to be ineffective in driving sales [26, 27, 12]. Also, several studies found that online movie reviews has no impact on box office performance [17, 15]. Valence does not affect the sales rank of books on Amazon [28]. Other studies show that while positive valence increases sales, negative valence does not jeopardize sales [5].

The effects of volume are also conflicted. The mere presence of customer reviews can have a positive effect on sales [12]. Others show that volume is positively related to sales volume and revenues [29, 30, 31]. Volume has also been shown to positively affect box office sales [32, 15], sales rank of electronic products [14, 33] and books [28], and purchase intention [34]. However, other studies suggest that the effect of volume alone is insignificant [25]. For example, Gopinath et al. [23] find that the volume of online WOM does not impact sales of cell phones, and Chintagunta et al. [21] show that volume does not have a significant impact on movie box office performance.

These inconsistencies can be attributed to the fact that volume does not exert a direct effect on consumers [6]. Higher volume implies more information [35] and an increased correctness of expressed opinion [36], since an opinion formulated by many others is often perceived as more objective and trustworthy [37]. Valence, on the other hand, conveys the collective opinion of a product to the reader. A large number of reviews thus lends support to the expressed opinion, increasing customers' confidence in the review information. Prior research in this domain lends support to this line of thought. Khare et al. [38] show that volume can have either a beneficial or harmful effect depending on the valence. While a higher volume of positive reviews increases preferences for the product, a higher volume of negative reviews decreases preferences. In addition, low volume can cause customers to doubt valence ratings and diminish the usefulness of reviews [6]. Hence, we believe that the effect of review valence should be examined in conjunction with other review characteristics that can moderate its impact on the customer decision making process. We therefore hypothesize a two-way interaction between volume and valence:

> H1: Valence has a positive effect on the probability of a purchase that is stronger when there are many reviews and weaker when there are few.

2.2. Exposure to reviews and product price

Retailers often display the volume and valence next to the image and price of product. However, there is no study that has looked at how the price of different products in a category interact with valence and volume to influence purchase decisions. In addition, potential customers who need more information must take further action such as clicking on a 'review tab' or scrolling down to read the reviews and see other summaries, such as a bar chart of star ratings. Although this additional action seems important, previous research has not considered this factor either. In this section, we explain how the effects of valence and volume of reviews on purchase decisions may be further moderated by additional information available on the retailer's website such as price and exposure to product reviews.

2.3. Effect of product exposure

Cognitive dual-process theories can help provide a comprehensive explanation of how reviews affect consumers' purchase decisions [18]. The Elaboration Likelihood Model (ELM) [39] suggests that people can process information using either a peripheral or central strategy. In a similar vein, the Systematic-Heuristic Model (HSM) [40] describes cognitive processing as either systematic or heuristic. On the one hand, when people have high motivation and resources to process detailed information, they follow the central (systematic) route. Central (systematic) processing involves a thorough reading of the message, considering and elaborating on (thinking about) all the available information and carefully evaluating all the available attributes. On the other hand, people generally follow the peripheral (heuristic) route of processing when they are not motivated to process a message. Here, they look for simple cues signaling the value of the object and base their judgements on simple decision rules (i.e., rules of thumb). According to HSM these two modes of processing can occur together [18].

Evans and Stanovich [41] suggest that, while central and peripheral strategies can process analytical and heuristic information respectively, individuals' modes of information processing can exist on a continuum. They go on to explain that while the inhibitory processes in systematic information processing can override the faster automatic route, a higher goal can necessitate the use of both types of information processing. They provide the example of a 'reflective mind' that attempts to collect all the information possible before reaching a conclusion. A reflective mind could be engaged in slow and careful processing but also in a quick and casual manner or any point in between. We believe these arguments play a vital role in explaining how heuristic and analytical cues interact to influence consumers' decisions.

People can generally be described as cognitive misers: They prefer to spend less cognitive effort and process information quickly than devote mental resources to demanding, deliberate thinking [42, 43, 44, 18]. Thus, unless they have a strong motivation to process more nuanced information, they may be expected to conserve their cognitive resources and rely on heuristic cues, which is line with the *principle of least effort* [45]. Both valence and volume, presented as numerical values, are heuristic cues. Since numbers are a primary way of storing information, they are easy to process [46] compared with reading and evaluating actual reviews, which are often nuanced and conflicting. Conversely, it is reasonable to assume that an individual who reads reviews is looking for more detailed information. Reading reviews increases elaboration, meaning that information is carefully considered. Therefore, consistent with dual-processing theories, when a person attempts to make a well-informed decision both heuristic and analytical cues are considered in the final evaluation of the product [47]. Consequently, we hypothesize a three-way interaction effect:

> H2: Valence (H2a) and volume (H2b) have a positive effect on the probability of a purchase that is stronger when prospective customers are exposed to reviews than when they are not exposed to reviews.

2.4. Effect of product price

Price is an important characteristic that can moderate the effect of reviews on purchase decisions. While evaluating the consideration set of products in a category, customers compare the observed point-of-purchase price with a reference price, which is generally the average market price of products in that category [48]. If the product's price is higher (lower) than an average price of products in the category, customers perceive such a product as (in)expensive. In addition, price can affect consumer involvement with the product and hence the decision, affecting the mode of information processing. Product involvement is generally expected to be higher when a product is more expensive, because a higher price is associated with higher risk and greater 'pain of paying' [49].

We posit that heuristic cues such as valence and volume will play a more influential role for purchase decisions involving higher-priced products. Prospect theory [50] states that people are generally loss averse since losses are psychologically painful. A bad purchase decision could result in psychologically costly losses and perhaps even monetary losses. In order to alleviate the possibility of such painful losses, consumers will prefer to collect all available information before making a decision. Consistent with dual processing theories, which suggest that a reflective mind considers heuristic and analytical cues, we hypothesize another three-way interaction effect between valence, volume and product price:

> H3: Valence (H3a) and volume (H3b) have a positive effect on the probability of a purchase that is stronger for higher-priced products within a category than for less expensive ones.

We have proposed three factors that moderate the effect of valence on purchase decision: volume, price and review exposure. These moderators could operate independently, for example, the valence effect on purchase of reading a review for a product that is more expensive could simply be the sum of the effects for reading a review and higher price, without higher-order interactions. Alternatively, they could interact with each other, where the combined effect of valence for reading many reviews and a higher price is greater (or lesser) than the sum of individual effects. In this case there would be higher-order interactions. In line with dual-processing theories, the customer who reads reviews is probably more involved with the decision and hence the effect of reviews on his attitudes and subsequent behaviors may be expected to be stronger, since the customer is going to evaluate the reviews carefully. When there are many reviews, the customer will trust valence more, because volume adds credibility to opinion expressed in the reviews [38]. Finally, this effect further depends on the price of the product: customers will consider reviews even more when the product is relatively expensive to neutralize the risk involved in the decision.

Our reasoning is in line with signaling theory. Consumers make decisions based on available information (e.g., on the website) and private information, which is available to only a subset of the public [51]. Hence, they do not have access to all information about the product, creating asymmetry. Signaling theory posits reduced information asymmetry between two parties [52], in our case consumers and the brand. Price constitutes the observable quality of the product, but there is also the unobservable quality, which can be signaled by consumer reviews [12]. As some previous studies show [53], the signals can have an additive effect with more signals (here price, valence, and volume) making customers more certain about their decision. Consistent with our previous hypotheses, we posit a four-way interaction:

> H4: The effect of valence on purchase probability increases with the number of reviews, and this effect grows even stronger when customers read reviews and the product's price is relatively high.

3. Empirical tests

We have two studies to test our hypotheses. Study 1 tests only H1, and Study 2 tests all of the hypotheses. The two studies use data from different companies in different categories. In both cases, we investigate how the effects of the independent variables are associated with the purchase probability using observed purchase data.

3.1. Study 1

Study 1 tests H1 using data from a company that provides unique, one-of-a-kind products, which are unusual in nature and often higher priced. This retailer also provides customer reviews on its website. We have data from January 4, 2015 to January 2, 2016. The data are summarized at the level of a SKU, which corresponds to a web page used to display the product. We include all the offered product categories (e.g., electronics, apparel, home and living, personal care, travel). Because the products are sold under the company's brand name, we do not need to control for the effect of a brand. The unit of analysis is the *exposure*, where a customer views the webpage for a SKU. We focus on exposures since we are ultimately interested in whether or not a customer purchased the SKU after viewing its webpage. In some cases, a customer visits the page for a SKU, then visits other pages, and returns to the page. When a customer visits a page multiple times during a calendar day we count it as a single exposure.

Table 1: Descriptive Statistics (Study 1 & Study 2)

	Study 1				Study 2			
Variable	Mean	SD	95% LCL	95% UCL	Mean	SD	95% LCL	95% UCL
Log Price	6.59	1.15	6.57	6.59	−0.28	5.62	−0.28	−0.29
Volume	12.88	21.70	12.87	12.89	39.64	86.77	39.54	39.74
Valence	3.61	1.18	3.61	3.61	4.19	0.72	4.19	4.19

We only include instances when reviews were exposed because visitors do not see volume unless they view reviews. This gives 2,598,060 observations. For each exposure we know the (1) number of reviews for the SKU, which we group into three categories (one review, two–four reviews, more than five reviews), (2) average number of stars (i.e., valence) across the reviews for the SKU, and (3) price of the SKU. Our dependent variable is a boolean value depending on whether or not an item was purchased. We estimate a logistic regression predicting purchase that tests the two-way interaction between review valence and volume, while controlling for price. Tables 1 and 2 give summary statistics.

Table 2: Frequencies (Study 1 & Study 2)

	Study 1		Study 2	
	Frequency	Percent	Frequency	Percent
Exposure				
No	8,545,194	76.68	2,522,615	88.59
Yes	2,598,060	23.32	324,764	11.41
Number of reviews				
One	2,344,260	21.04	356,554	12.52
Two–four	3,122,628	28.02	500,781	17.59
Five+	5,676,366	50.94	1,990,044	69.89
Price				
Low			1,546,657	54.32
High			1,300,722	45.68

3.2. Study 1: Results

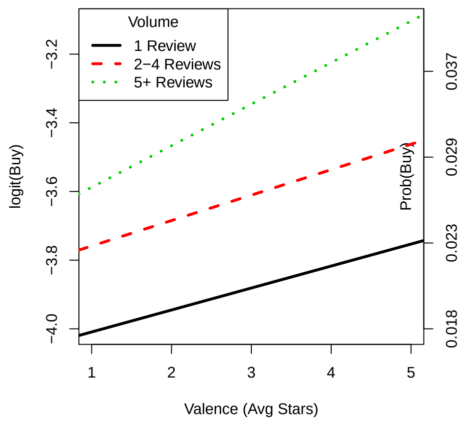
We use a logistic regression to test our predictions and assess the impact of review features on purchase probability. The model includes the independent variables (i.e., review valence, volume) and the control variable (i.e., logged price). Our results show that the two-way interaction effect is significant ($\chi^2_2 = 51.48, p < .0001$), indicating that the two factors exert an interdependent effect on the probability of purchase. Table 3 displays all the parameter estimates obtained from the logistic regression.

Table 3: Estimates (Study 1)

Parameter		Estimate	S.E.	Wald χ^2	P
Intercept		−1.8781	0.03110	3641.5741	< .0001
Valence		0.12100	0.00619	382.5518	< .0001
Volume	1	−0.3644	0.03290	122.7237	< .0001
Volume	2–4	−0.1241	0.03340	13.8265	0.0002
Val*Vol	1	−0.0570	0.00832	46.9984	< .0001
Val*Vol	2–4	−0.0469	0.00875	28.7606	< .0001
Price		−0.2778	0.00320	7537.0611	< .0001

As Table 3 shows, the effects of valence for one review ($\beta = -0.06, p < .0001$) or two–four reviews ($\beta = -0.05, p < .0001$) is smaller than the effect of at least five reviews. Figure 1 illustrates the interaction effect and shows the effect of valence on purchase probability is the strongest when there are many reviews, thus lending support to H1.

Figure 1: Illustration of interaction effects (Study 1) assuming an average logprice of 6.59.



3.3. Study 2

We corroborate Study 1 and test the other hypotheses with data obtained from an internet-only retailer that sells health and beauty products. We have 15 weeks of purchase data from June 29 to October 11, 2014. The retailer carries thousands of stock keeping units (SKU), which corresponds to a web page used to display the product. Each SKU is assigned to a single *category*, and also a *brand*, for example, an 8 oz bottle of Pantene shampoo is assigned to the shampoo category and the Pantene brand. We include 76 categories (e.g., shampoos, styling products, face-creams, vitamins, supplements) and restrict our attention to the most popular brands (constituting about 50% of sales in a category).

There are 2,847,379 observations (i.e., SKU exposures). For each exposure we know (1) the number of reviews for the SKU, which we group into three categories: one review, two–four reviews, more than five reviews, (2) the average number of stars (i.e., valence) across the reviews for the SKU, (3) whether the customer clicked on the 'review tab' (i.e., was exposed to the reviews), and (4) product price, operationalized as a dummy indicating if the price was greater than the average in the category. Tables 1 and 2 give summary statistics. Our dependent variable is whether or not an item was purchased on the *same day* as the exposure. Thus, our analysis allowed for the possibility that a customer viewed a review and returned later in the day to purchase the product. We also allowed for longer periods and the substantive conclusions did not change.

3.4. Study 2: Results from logistic regression

We use a logistic regression to test our predictions and assess the impact of review features on purchase decisions. The model has four independent variables (i.e., review valence, volume, exposure, and product price) and all possible two-, three- and four-way interactions between these variables. The variable "PriceLow" is a dummy that equals one for lower-priced products within a category and zero for higher-priced products. Likewise, "ExposureNo" equals one if the visitor was not exposed to reviews and zero if so. For volume there are dummies for one review and two–four reviews, with five or more reviews as the base category. The four-way interaction effect is significant ($\chi^2_2 = 16.59, p = .0002$), indicating that the four factors exert interdependent effects on the probability of purchase. Hence, we do not dwell on the main effects or lower-order interactions, but first focus on the four-way interaction effect and subsequently on the net effect of each independent variable. Table 4 shows all the parameter estimates obtained from the logistic regression.

As Table 4 shows, the effects of valence for one review ($\beta = -0.17, p = .0072$) or two–four reviews ($\beta = -0.27, p < .0001$) of an expensive product when read by the customer is smaller than the effect of at least five reviews. Note that the negative signs do not mean that the effect of valence is negative, but that the effect is smaller than for having five or more reviews (the valence slope for one review, lower price, exposure to review text is $0.8444 - 0.6600 - 0.3218 + 0.4054 = 0.2680$ and the slope for two–four reviews, higher price, no exposure is $0.8444 - 0.2245 - 0.5522 + 0.1690 = 0.2367$). This supports H4—the effect of valence on purchase probability increases with the number of reviews, when customers read reviews and the product's price is relatively high. To disentangle the interaction effects we calculate slopes for different combinations of exposure, price and volume (Table 5).

Figure 2 shows the effect of valence on the logit of buying for each level of volume (different lines) and different combination of exposure and price (different plots). The slopes and intercepts are from columns four and five of Table 5, and the last five columns give the estimated conversion

Table 4: Estimates (Study 2)

Parameter	Volume Level	Estimate	S.E.	Wald χ^2	*P*
Intercept		−6.5941	0.1579	1743.16	< .0001
ExposureNo		1.3710	0.1643	69.59	< .0001
Valence		0.8444	0.0364	536.69	< .0001
Valence*ExposureNo		−0.2245	0.0379	35.14	< .0001
Volume	1	3.0058	0.1967	233.54	< .0001
Volume	2–4	2.4988	0.2147	135.40	< .0001
Volume*ExposureNo	1	−1.2443	0.2067	36.25	< .0001
Volume*ExposureNo	2–4	−1.0312	0.2260	20.83	< .0001
Valence*Volume	1	−0.6600	0.0450	215.14	< .0001
Valence*Volume	2–4	−0.5522	0.0502	121.21	< .0001
Val*Vol*ExpNo	1	0.2314	0.0472	24.08	< .0001
Val*Vol*ExpNo	2–4	0.1690	0.0526	10.31	0.0013
PriceLow		1.4425	0.1914	56.83	< .0001
ExpN*PriceLow		−0.3966	0.1990	3.97	0.0462
Valence*PriceLow		−0.3218	0.0443	52.69	< .0001
Val*ExpN*PriceL		0.1008	0.0460	4.79	0.0286
Volume*PriceL	1	−1.8875	0.2707	48.60	< .0001
Volume*PriceL	2–4	−2.5120	0.2772	82.11	< .0001
Vol*ExpN*PriceL	1	0.6938	0.2849	5.93	0.0149
Vol*ExpN*PriceL	2–4	1.2001	0.2917	16.93	< .0001
Val*Vol*PriceL	1	0.4054	0.0610	44.23	< .0001
Val*Vol*PriceL	2–4	0.5843	0.0644	82.23	< .0001
Val*Vol*ExpN*PriceL	1	−0.1723	0.0641	7.23	0.0072
Val*Vol*ExpN*PriceL	2–4	−0.2666	0.0677	15.51	< .0001

probabilities, which are shown on the right axes of Figure 2. Valence slopes are positive for all combinations of exposure, price and volume, but the effect is strongest when (1) there are many reviews (supporting H1), (2) customers read the reviews (supporting H2), and (3) the price is high (supporting H3). In fact, the valence slope is more than four times as steep when all three are true (β = 0.844) compared with when none of them are true (β = 0.203). Figure 2 illustrates the weaker effect of valence as combinations of the other three conditions are not met. For lower-priced products with fewer than five reviews and lack of exposure, that is, the customer does not read reviews, the effect of valence is fairly flat, indicating that valence has little effect on the purchase decision, although it is still positive. The slopes and graphs also show a difference between lower- and higher-priced products with different volumes: for high-priced products, the valence slope for five plus reviews increases substantially over fewer reviews, but for low-priced products the valence slopes for two–four and five plus reviews are nearly identical. The conclusions are summarized in Table 6.

3.5. Sensitivity analysis

We performed a sensitivity analysis to quantify the net effect of each variable on conversion probability. We first used the results from the logistic regression and computed the purchase probabilities for different values/levels of the independent variables (last five columns of Table 5),

Table 5: Slopes (Study 2) and estimated conversion rates for different valence values

Exposure to Reviews	Price	Number of Reviews	Inter-cept	Slope	Estimated Conversion Rate (%) Valence Value 1★	2★	3★	4★	5★
No	High	1	−3.46	0.191	3.66	4.40	5.28	6.32	7.55
		2–4	−3.76	0.237	2.88	3.62	4.54	5.69	7.10
		5+	−5.22	0.620	0.99	1.83	3.35	6.05	10.68
No	Low	1	−3.61	0.203	3.21	3.91	4.75	5.76	6.96
		2–4	−4.02	0.333	2.44	3.37	4.65	6.37	8.67
		5+	−4.18	0.399	2.24	3.29	4.83	7.03	10.13
Yes	High	1	−3.59	0.184	3.22	3.84	4.59	5.46	6.50
		2–4	−4.10	0.292	2.18	2.90	3.85	5.09	6.70
		5+	−6.59	0.844	0.32	0.74	1.69	3.85	8.53
Yes	Low	1	−4.03	0.268	2.26	2.94	3.81	4.92	6.34
		2–4	−5.16	0.556	0.99	1.70	2.93	4.99	8.38
		5+	−5.15	0.523	0.97	1.62	2.70	4.47	7.32

e.g., the conversion rate is 7.55% for no exposure, high price one review and 5 stars. We then changed the value of one focal variable at a time and computed the percentage change in the purchase probability.

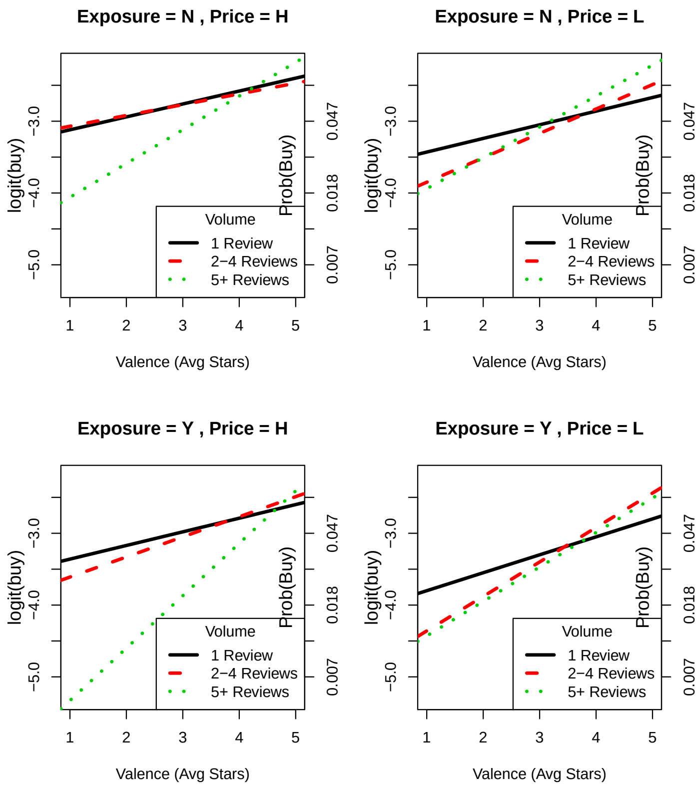
The effects of an increase in valence by one star are shown in Figure 3. We specifically looked at two different changes in valence, from three to four stars and then from four to five stars. The story is consistent with the discussion of the slopes and interaction plots (Figure 2). The largest percent changes are for higher-priced products with five plus reviews and exposure, where a unit change in valence is associated with over a 120% increase in conversion rate. The second highest is also for higher-priced products with five plus reviews, but no exposure, with percentage increases around 80%.

The net effect of change in review volume is shown in Figure 4. Here too, we looked at two different changes in reviews, from one to two–four reviews and then from two–four reviews to at least five reviews. The largest percent changes are shown in the upper left panel for higher-priced products and increasing from two–four to five plus reviews. Recall that Figure 2 shows large differences in the slopes between the green lines (five plus reviews) and the red lines (two–four reviews). In this panel, increasing to five plus reviews is associated with a 50.5% increase in conversion rate for five-star and no exposure, and 27% for five reviews and no exposure. We also see with low stars, increasing the number of reviews (and thus the credibility of the reviews) decreases conversion rates, e.g., by −85% for one star with exposure, and −65% for one star and no exposure.

The lower right panel of Figure 4 shows the second most variation in percentage changes, suggesting that for lower-priced products an increase in volume from one to two–four reviews implies large changes in the effects of reviews. This is consistent with the right two plots of Figure 2 with the differences in slopes between the black line (one review) and the red and green lines (2 plus reviews).

The results from the sensitivity analysis for exposure to reviews are in Figure 5. We compared the probabilities of purchase resulting from whether a customer reads the reviews or not for different values/levels of the other independent variables. All percentage changes are negative,

Figure 2: Illustration of the interaction effects



which we explain with decision uncertainty. Those looking at reviews are likely more uncertain about their decision and actively seeking more information from reviews. The overall story is consistent with our other plots.

4. Discussion

Online customer reviews are believed to affect customers' purchase decisions. Although previous research into the effects of different review features is vast, the results are mixed. In addition, extant literature on interactions between different review and product features as well as the role of review exposure is limited. Finally, previous research has often failed to focus on purchase decisions; if it has, it has been mostly for experiential products such as movies or books. Hence, the main objective of this study was to understand how review characteristics (i.e., valence and volume), product characteristics (i.e., price) and customer behaviors (i.e., reading reviews) interact with each other to influence purchase decisions.

Table 6: Summary of hypotheses

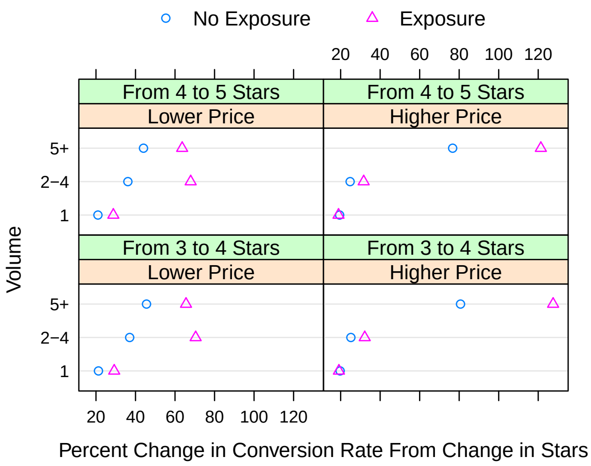
Hypothesis	Result
H1: Valence has a positive effect on the probability of a purchase that is stronger when there are many reviews and weaker when there are few.	Supported
H2a and b: Valence and volume have a positive effect on the probability of a purchase that is stronger when prospective customers are exposed to reviews than when they are not exposed to reviews.	Supported
H3a and b: Valence and volume have a positive effect on the probability of a purchase that is stronger for higher-priced products within a category than for less expensive ones.	Supported
H4: The effect of valence on purchase probability increases with the number of reviews, and this effect grows even stronger when customers read reviews and the product's price is relatively high.	Supported

4.1. Theoretical implications

We expected the effect of valence on purchase decisions to increase with volume, and this effect to grow even stronger when customers read reviews of higher-priced products. We found that the effect of valence on purchase decisions is positive, which is in line with the majority of prior research [21, 54], but the magnitude of the effect depends on other factors. For example, consider customers who do not read reviews and hence make purchase decisions using peripheral cues, namely valence and volume. We see that the effect of valence, regardless of its value, is marginal when there is only one review irrespective of the product's price, suggesting that customers find one review insufficient to make an informed decision. This result suggests that heuristic cues indicating quality and popularity work together. From an information processing point of view, this result also suggests that heuristic cues typically stimulating peripheral processing may in fact stimulate central processing when the information from these cues is inconsistent.

The study also has important implications for academics studying the effect of price in online environments. We find that when customers shop for a relatively less expensive product, the effect of valence becomes steeper already with a small increase in the number of reviews (i.e., two to four reviews) and the same is true for more than five reviews. Hence, for such products having a moderate number of reviews is as beneficial as having a large number of reviews. However, when customers shop for a more expensive product, there needs to be more reviews (e.g., above five) for valence to have an effect, showing that higher-priced products need a larger number of reviews. In addition, when the price of the product is high and customers read reviews, many negative reviews can reduce purchase probability. These findings suggest that when the risk related to the purchase decision is low, customers need less information to support their decisions. The fact that the effect of valence becomes stronger when the product is more expensive and there are more than five reviews implies that customers associate such a purchase with higher risk and need more reviews to make a decision. These findings can be explained using prospect theory [50], which states that people are generally risk-averse. Individuals may be more willing to take a risk and purchase a product that has not been reviewed by many customers (i.e., volume) or the reviews are not that positive (i.e., valence) when the prospective losses are small, as it is with lower-priced products. However, customers need much more information (i.e., volume) and more reassurance of the quality of the product (i.e., valence) when potential losses are more

Figure 3: Sensitivity analysis examining a change of one star (valence)



severe, as it is with higher-price products. Academics studying pricing strategies in e-commerce websites should therefore also examine the moderating impact of other variables in the digital environment.

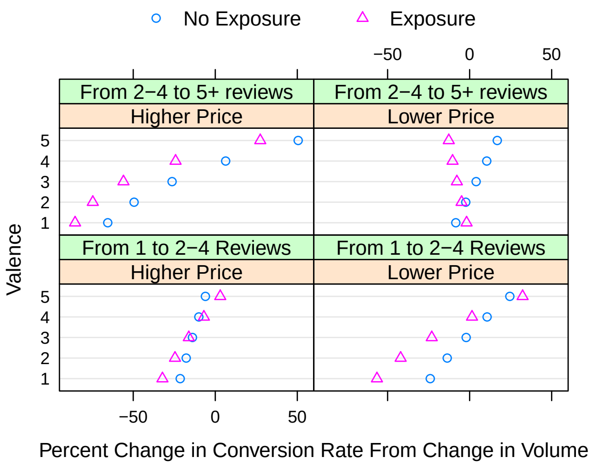
One of our objectives was to examine the impact of reading reviews, a behavior that has not been examined in extant research. When customers use central processing by reading reviews, the effects of valence and volume become stronger, especially for higher-price products. This is in line with dual-processing theories. When the risk associated with the decision is high, consumers employ a central (systematic) processing strategy. The findings further strengthen the argument that peripheral cues can influence central processing [47]. A surprising result was that when customers read reviews, they become less willing to purchase the product. A common belief is that customers read reviews to reduce the risk associated with a purchase. However, we find that in many cases reading reviews fail to do so.

In conclusion, the context of this study makes it unique from prior work and the findings make a significant contribution to ongoing work in the domain of online reviews.

4.2. Implications for retailers and manufacturers

The implications for retailers are different from manufactures of the products distributed by the retailer. The retailer should be primarily interested in having a satisfied customer who will return in the future. It should be less interested in whether the customer buys brand A or B in some category, as long as whichever brand the customer buys provides a high level of utility. Having insightful and accurate customer reviews should improve the shopping experience and the chance that the customer will find a product that delivers utility. Negative reviews for poor products are desirable because they help customers find the right product for their needs (assuming the customer buys another brand in the category from the retailer). Thus, it is in the retailer's interest to have an accurate and unbiased review ecosystem. Any efforts to manipulate the review system may damage its credibility, and drive customers to a retailer that has unbiased

Figure 4: Sensitivity analysis examining a change of volume



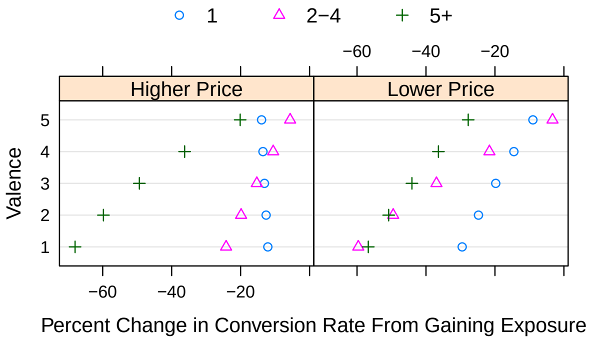
reviews. That said, these findings help the retailer prioritize when they should actively solicit reviews, both positive and negative. It is more important to have reviews for the premium, higher-priced products within a category, but also for products where there is more likely to be uncertainty. For example, we predict that having reviews is less important for a well-known brand than for an unknown one. Consumers are also more likely to be uncertain about a new product category than for established ones. There may also be more uncertainty with more complicated products than with simple ones. At the same time it is important to note that mere exposure to reviews does not necessarily increase the probability of a purchase. The review ecosystem should be designed such that a potential customer is able to obtain relevant information easily without experiencing cognitive overload.

The implications for the manufacturer are different, since a manufacturer wants consumers to buy its brand rather than a competing brand sold on the retailer's website. Our findings provide insights on the conditions when reviews will have the strongest effect on purchase probability—many reviews, higher-priced products, consumers are reading reviews—again prioritizing when manufacturers should be concerned. Having *many* negative reviews reduces the chance of purchase. Manufacturers should therefore carefully track online reviews for negative comments, quickly reach out to aggrieved consumers and thus limit the potential damage from negative word-of-mouth. In some cases, negative reviews could be constructive and provide ideas for product improvements and/or extensions.

4.3. Limitations and future research

Although our study has important findings, it is not without limitations. We analyzed data from two retailers operating in different categories, but it is desirable to corroborate our findings by examining additional categories such as appliances (washing machines, stoves, etc.), which have much higher price points. We included two review features, one product characteristic and one behavioral measure. However, other consumer- and review-related factors can be at play

Figure 5: Sensitivity analysis examining a change in exposure



here, such as review helpfulness and recency [55]. Another factor that could affect the decision to read reviews is whether the consumer has purchased the product before, e.g., a consumer who has purchased before will be less likely to read reviews, and reviews will have less effect since the consumer has first-hand experience with the product. Reviews should have stronger effects on customers new to the brand and/or category. Future studies should investigate the role of these characteristics to account for consumers' prior brand knowledge, attitudes and preferences.

In addition, consumers are becoming aware that companies can create fake reviews or stimulate positive reviews with financial rewards [56]. This may diminish the credibility of online reviews and customers may not trust extremely positive reviews [57, 24, 58]. Future studies may want to account for the nonlinear effects of review characteristics.

Finally, even though we studied consumers' interactions with reviews, we did not examine the content of the reviews. A sentiment analysis of online reviews and its effect on purchase decisions would be an interesting endeavor for future work in this domain. Hu [55] suggest that purchase decisions are affected by review rating via its sentiment. This is similar in spirit to this study which states that consumers attempt to process information of different types from different sources before reaching a purchase decision.

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