Impact of Review Emotions on Sales: The Moderating Role of Product Type

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ABSTRACT

Online reviews provide product information and express consumers' emotions. In this paper, we examine how review-embedded emotions and product type (search vs. experience) affect sales on Taobao – a leading online shopping website in mainland China. First, our findings indicate that some emotions, such as regretful and trustful, contained in consumer reviews would affect product sales. Second, we have found that product type would affect sales, which would also moderate the effects of emotions on sales. Based on the results, we suggest that not all review emotions are equally important, regarding their potential effects on sales. Our work would make several significant contributions to existing literature on e-commerce and user-generated content. In the meantime, this work would provide meaningful implications for online review platforms, review providers, and review users.

Keywords: Consumer Reviews, E-Commerce, User-Generated Content, Product Sales.

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1. INTRODUCTION

Online reviews could affect consumers purchase decisions. With the rapid development of internet technologies, online product reviews have become valuable resource for consumers to collect and utilize product-related information during purchase decision making processes. Firms would like to make great efforts to encourage their consumers to create and post reviews about their products online, for various strategic purposes,

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such as enhancing consumer engagement and increasing purchase intention (Godes and Mayzlin, 2009; Kshetri and Jha, 2016). In particular, firms could manipulate online reviews in attempts to influence consumers' purchase decisions, which has been demonstrated in past research (Dellarocas, 2006). By construing online reviews, including the good and the bad about a product, consumers become more knowledgeable about the product, without any direct experience with it.

In line of Information Systems (IS) research, researchers studying online review systems have extensively discussed how online reviews affect consumer decisions. But, the economic impact of disseminating online reviews, essentially why online reviews matter, has been relatively insufficient in past research. Online reviews are commonly involved in experimental studies to understand how reviews affect consumer perceptions, including purchase intentions and related judgments (Kim and Gupta, 2012). However, there has been little research that has directly addressed the effect of reviews on sales. In those studies, exploring the relationship between reviews and sales, mixed findings are found. For example, Chevalier and Mayzlin (2006) have found that online consumer ratings could significantly affect book sales on Amazon. By contrast, Duan, Gu, and Whinston (2008) have found no significant effect of the rating of online reviews on movies' box office revenues. So, the aim of this research is to further explore the effects of online reviews on sales.

To research online reviews, we follow past studies that emphasize the important role of review emotions affecting consumer perceptions and purchase decisions (Yin et al., 2017). In the current work, we explore whether various review emotions, such as satisfied and regretful, would significantly affect product sales. We suppose this research question is challenging and interesting.

Based on our results, we suggest that certain emotions embedded in online reviews could affect sales. Meanwhile, our results indicate that product type could affect sales and moderate the effects of emotions on sales.

2. THEORETICAL DEVELOPMENT

2.1 Electronic Word-of-Mouth

Consumers search for information prior to making a purchase decision (Hennig-Thurau et al., 2003). Specifically, consumers search and collect information, evaluate alternatives, and finalize their decisions (Payne et al., 1991). There are two types of information provided online, seller-created product attribute information and user-created review information. Studies have recognized the power of consumer reviews and found that consumers feel more confident and trustful to rely on peer reviews rather than firm-generated-content.

As claimed above, the important role of electronic word-of-mouth (eWOM) in consumer decision making has long been recognized in research and practices. Given the convenience of online shopping, e-commerce has developed rapidly, and consumers nowadays are heavily relying on online product reviews to make purchase decisions.

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Also, consumers are encouraged to rate the product they have purchased and express opinions about the product characteristics they have experienced. So, it becomes necessary for researchers to study online reviews from many different aspects.

2.2 Review-Embedded Emotions

Both informational and emotional content of reviews would affect consumer perceptions and decisions. Reviews have been investigated from many different aspects, such as review valence and volume of reviews (Chevalier and Mayzlin, 2006; Ghose and Ipeirotis, 2006). A previous study claims that emotional discussions could affect people more than cognitive discussions, with distinct emotions presenting differential effects (Song et al., 2016). Also, reviews containing certainty emotions are perceived to be more helpful than reviews containing uncertainty emotions (Ahmad and Laroche, 2015). Furthermore, Berger and Milkman (2012) suggest that emotional review content has not been sufficiently studied. In their recent research, the researchers have found the significant associations between emotions and information sharing behavior through *New York Times* website. Accordingly, in the current work we follow past research and focus on emotions to explore the effects of product reviews on sales.

To better understand review emotions, we follow literature mainly arguing that emotions affect a variety of human behaviors, yet not all emotions are equal. Traditionally, emotions expressed by consumers could be classified according to valence, being positive and negative. Both positive and negative emotions embedded in online reviews would potentially affect product sales (Derbaix, 1995). Furthermore, researchers suggest that negative emotions are considered as more irrational and therefore would be less likely to affect consumers' evaluations (Kim and Gupta, 2012). But, referring to negativity bias, other researchers argue that negative reviews would have stronger effects on product sales than positive reviews (Chakravarty et al., 2009). In this line of research, Yin, Bond, and Zhang (2017) have researched various negative emotions expressed in online reviews and suggested the differential effects of these discrete emotions, such as anger and anxiety, on perceived review helpfulness. In the current work, we would like to take a close look at emotions, by examining the differential effects of positive and negative review emotions on sales.

2.3 Product Sales Impact

In contrast to past research exclusively focusing on consumer perceptions, such as product evaluations and review helpfulness, in this study we would like to emphasize the business impact of review emotions (Kim and Gupta, 2012; Yin et al., 2017). It is because the economic outcomes of online reviews have been relatively underexplored. On the one hand, user-generated-content would interact with seller-created-information to affect consumers' purchase decision and helps them identify the products that best fit their idiosyncratic purposes (Chen and Xie, 2008). On the other hand, we have noticed that few past studies have directly related sales to online user-generated-content. As Goh, Heng, and Lin (2013) have stated, the empirical evidence to demonstrate the economic values of social media content is limited. There

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are few exceptions that we would like to address. For example, Ghose and Ipeirotis (2011) have explored the multiple aspects of review text, such as review subjectivity and readability, and their impact on sales. Also, they have found these features could effectively predict sales. It is important to emphasize that, in the current work we would only address emotions embedded in online reviews in relation to sales. Despite the mainstream belief claims that reviews affect sales by sharing informational content purposely, in this study we would like to explore the other side of reviews – emotional review content.

In past research exploring the effects of content- and emotion-features on sales, product type could be a moderator (Huang et al., 2013). However, there has been a lack of empirical studies that demonstrate how these effects vary across product categories. For example, a researcher has defined low- and high-involvement products (Lastovicka, 1979).

Particularly, for low-involvement products, consumers would perceive little linkage to important values; whereas, for high-involvement products, the perceived product value and purchase risk would be relatively high. Consumers go through different decision-making processes according to product involvement (Assael, 1984; Engel et al., 1993). Previous studies on product reviews have also proposed that consumers construe the reviews of search (emphasizing objective experiences) versus experience (favoring subjective experiences) products differently. For example, it has been demonstrated that consumers would rely more on reviews to make purchase decisions for experience products than for search products (Park and Lee, 2009). However, past research has also found that consumers would buy products with subjective or emotional content only for search but not experience products (Ghose and Ipeirotis, 2011). The mixed findings in literature have motivated us to further explore the distinction between product categories (e.g., search vs. experience) in the current study.

To sum up, we would like to test the relationships between review emotions and product sales in this study, by considering the moderating effect of product type. Based on past literature, we have developed a research model presented in next section.

3. RESEARCH MODEL AND HYPOTHESES

Following the literature, we have reviewed, we propose a research model to mainly explore: 1) the main effects of review-embedded emotions on product sales, and 2) the moderating effect of product type, by considering search versus experience products. Figure 1 shows the proposed research model based on previous discussion.

From marketers' perspective, online reviews are most important if they could affect product sales. To further clarify the effect of product reviews on sales, we would like to focus on review-embedded emotions, although we would not suggest anyone to neglect the potential effect of review content.

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Regarding review emotions, researchers usually emphasize review valence, being positive, neutral, or negative. But, it is not clear to us whether positive and negative reviews would be equally significant to affect sales. Specifically, there has been little evidence to show whether negative reviews are more salient than positive reviews, in terms of sales impact. As discussed earlier, studies have presented mixed findings about the effects of positive reviews versus negative reviews on review effort. So, we believe in this study we should address the comparison between positive and negative emotions extracted from online reviews, in terms of their effects on product sales.

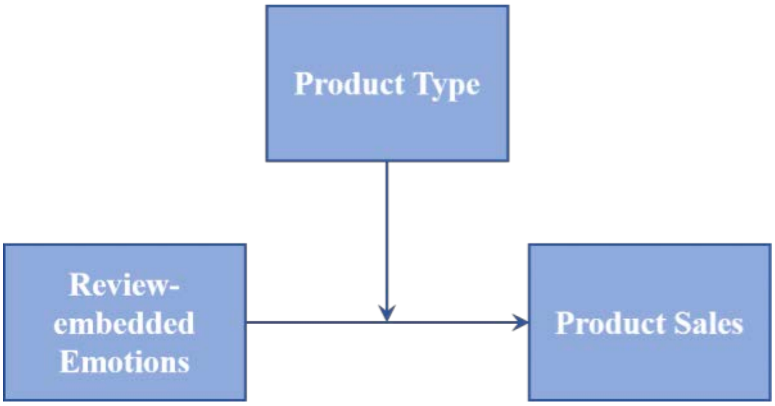

Figure 1. We propose that product sales would be affected by review-embedded emotions and product type

Indeed, good products usually receive positive reviews, which in turn show a positive relationship with sales. Similarly, bad products receive negative reviews, which in turn show a negative relationship with sales. Regarding the effects of review emotions on product sales, we develop ***H1*** and ***H2*** for our empirical test, as shown below.

> ***H1****: Positive emotions embedded in online reviews would positively affect product sales.*
> ***H2****: Negative emotions embedded in online reviews would negatively affect product sales.*

Furthermore, based on negativity bias, we would like to explore if negative reviews are more influential to sales than positive reviews, as stated in ***H3***.

> ***H3****: Negative emotions embedded in online reviews would be more likely to affect product sales than positive reviews.*

In addition, past studies have widely recognized the moderating effect of product type on the relationship between online reviews and consumer decisions. Thus, we think

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it is necessary to consider product type, search versus experience, in our model. Thus, we predict in ***H4*** and ***H5*** that for experience products consumers are more likely to be affected by review-embedded emotions.

> ***H4****: Negative emotions would be more likely to affect sales of experience products than search products.*
> ***H5****: Positive emotions would be more likely to affect sales of experience products than search products.*

4. METHODS

4.1 Data Collection

We have collected review data and sales data from Taobao (*www.taobao.com*) – one of the most popular online shopping websites in mainland China. Accordingly, Taobao shoppers are chosen as the main target population. Similar to Amazon.com, Taobao allows consumers to create and post reviews on the platform, which become visible to prospective consumers while considering a purchase of the reviewed product. In this study, we have created a panel data set of products belonging to two product categories, search versus experience. We have selected four products falling into the two categories, by considering product popularity and total number of reviews. To specify, we think it is necessary to ensure that the selected products have been reviewed by at least 10,000 consumers. Also, in order to obtain sufficient amount of valid data, we would like to confirm that these products are in stock on Taobao during data collection period. Figure 2 shows a sample review collected for one of the products selected for this study.

The four products in our sample include sneakers (Experience #1), men's underwear (Experience #2), electric kettle (Search #1), and rice cooker (Search #2). Over the period from January 20 to April 10, 2018, sales data has been collected every 30 minutes and aggregated to daily. We have also collected all reviews of each selected product to capture review emotions. Among the reviews displayed on the website in a recommended order set by Taobao, the top 100 reviews have been sampled. The rationale is that, average consumers would be most likely to process the top 100 reviews at maximum for making a purchase decision. For a specific day, the collected reviews should be coded for extracting emotions and then collapsed. Data has been collected and validated by taking the following attempts: 1) a web crawler developed by Python is used to retrieve inventory data reflecting sales, 2) the days with abrupt change of inventory are intentionally removed, and 3) computed daily sales based on inventory

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change is closely monitored and compared to observed sales which is the difference of displayed number in stock between days.

Figure 2. A screenshot of sample review of Nike Air Force 1 sneakers

In particular, before aggregating to daily sales, we have removed the potentially problematic 30-minute sales data signaled by unexpected change of inventory. We consider the following two scenarios: 1) inventory increases by replenishment, so sales data becomes unavailable, and 2) inventory decreases sharply for unknown reasons, resulting in sales more than three standard deviations above the average sales of the day. In both cases, we are intended to replace the original unexpected values by the average. Again, we have been outstandingly cautious when collecting data using automated tools, without arbitrarily overlooking any noises caused by technical or unknown issues. In addition, in our data set a day's sales is coupled with the aggregate of 100 reviews collected from one day before. In other words, we consider one-day lag between reviews updated daily and sales as a consequence of processing present reviews.

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Although past studies have considered different time lags to examine similar research questions, from our observation Taobao usually refreshes reviews for each product on daily basis, so we think one-day lag is justified.

4.2 Review Coding

We have coded the reviews mainly for extracting review-embedded emotions. As past research has suggested, emotions could be divided into multiple categories, such as anger, disgust, fear, happiness, sadness, and surprise (Ekman, 1992). Accordingly, researchers have attempted to extract emotions from various forms of online text.

The lexicon used in the current study is developed and provided by the information retrieval lab from Dalian University of Technology (*ir.dlut.edu.cn*), as proposed in past research (Xu et al., 2008). Given the relatively limited lexicons currently available for us to analyze sentiment of Chinese text, we consider our task challenging but pioneering. To justify, we have selected this lexicon as it is well based on emotion literature and has been previously tested in empirical studies exploring research questions similar to ours (Guo and Zhang, 2016; Yang et al., 2016). To the best of our knowledge, the current study is one of the few empirical studies using the lexicon mentioned above to analyze Taobao reviews.

In R programming environment, we have formulated an automated process incorporating the lexicon to identify review-embedded emotions and compute scores for each of the emotions categorized. Based on the lexicon, we have extracted emotions belonging to twenty-one categories, including happy, satisfied, sad, angry, scared, etc. We then compute daily emotion score by multiplying the frequency of a specific emotion by its corresponding intensity provided by the lexicon. All emotions are quantified on daily basis.

$$Emotion\ Score = Frequency * Intensity\ of\ Emotion$$

Aligned with our research model shown in Figure 1, the variables regarding emotions, product type, and sales are constructed and operationalized, as shown in Table 1.

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Variable	Type	Description
Emotion score	Continuous	Frequency and intensity of emotion.
Product type	Binary	1 = experience, 0 = search.
Sales	Continuous	Daily change of inventory.

Table 1. List of variables collected and coded for our study

4.3 Model Specification

To test our hypotheses, we adopt a multiple linear regression model by considering the interaction between review-embedded emotions and product type. It is important to emphasize that the unit of observation in our data set is by date, so that sales, reviews, and review- embedded emotions are all aggregated on daily basis.

We suppose that not all emotions identified should be included in our model if not significantly correlated to sales. So, we decide to select emotions that are moderately or highly correlated with sales at least in one product. As shown in Table 2 and Table 3, seven of the twenty-two emotions previously identified and sales are summarized with their between-variable correlations.

	ND	NE	NH	NO	PA	PG	PK	Sales	Notes
ND	1.00								Selected emotions are as follows. - ND: Hateful. - NE: Anxious. - NH: Regretful. - NO: Angry. - PA: Happy. - PG: Trustful. - PK: Wishful.
NE	.22 *	1.00							
NH	.04	-.04	1.00						
NO	.07	.70 ***	.14	1.00					
PA	.26 **	.03	.01	-.07	1.00				
PG	.10	.05	-.03	-.15	.29 ***	1.00			
PK	-.19 *	.01	-.06	-.09	.17	.08	1.00		
Sales	-.14	.14	.11	.09	.05	.24 **	.33 ***	1.00	

Table 2. Correlations between emotions and product sales for search products (n = 128)

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	ND	NE	NH	NO	PA	PG	PK	Sales	Notes
ND	1.00								Selected emotions are as follows. - ND: Hateful. - NE: Anxious. - NH: Regretful. - NO: Angry. - PA: Happy. - PG: Trustful. - PK: Wishful.
NE	.48 ***	1.00							
NH	.40 ***	.58 ***	1.00						
NO	.26 **	.44 ***	.11	1.00					
PA	.39 ***	.32 ***	-.05	.51 ***	1.00				
PG	.39 ***	.36 ***	.03	.52 ***	.46 ***	1.00			
PK	.11	.09	.23 **	.18 *	.21 *	.23 **	1.00		
Sales	.14	.09	-.15	.23 **	.25 **	.32 ***	-.02	1.00	

Table 3. Correlations between emotions and product sales for experience products (n = 131)

Our model is specified as follows.

$$\begin{aligned} Sales = {} & \alpha + \beta_1 * Hateful + \beta_2 * Anxious + \beta_3 * Regretful + \beta_4 * Angry + \\ & \beta_5 * Happy + \beta_6 * Trustful + \beta_7 * Wishful + \beta_8 * Hateful * Product + \\ & \beta_9 * Anxious * Product + \beta_{10} * Regretful * Product + \\ & \beta_{11} * Angry * Product + \beta_{12} * Happy * Product + \\ & \beta_{13} * Trustful * Product + \beta_{14} * Wishful * Product + \beta_{15} * Product + \varepsilon \end{aligned}$$

The summary statistics of the data for search and experience products are presented in Table 4 and Table 5, respectively.

Variable	Mean	Std.Dev.	Min	Max
ND	10.96	6.83	0	30
NE	9.88	12.64	0	77
NH	1.81	3.51	0	15
NO	2.75	3.44	0	16
PA	32.98	14.15	8	93
PG	93.33	32.73	38	254
PK	30.23	13.71	5	70
Sales	148.10	180.07	11	1498

Table 4. Descriptive statistics of emotions and sales for search products (n = 128)

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Variable	Mean	Std.Dev.	Min	Max
ND	9.61	6.40	0	42
NE	8.80	8.91	0	41
NH	2.60	3.69	0	14
NO	1.37	2.34	0	9
PA	90.15	26.95	49	248
PG	29.24	21.49	0	81
PK	10.84	7.81	0	37
Sales	342.60	261.11	43	1560

Table 5. Descriptive statistics of emotions and sales for experience products (n = 131)

So far, we have introduced model specification along with the variables included in the model, based on the research model we have proposed earlier. In next section, we present the results of our analysis.

5. RESULTS

The main goals of our analysis are to examine: 1) the effects of review emotions on sales, 2) the effects of product type (search vs. experience) on sales, and 3) the interaction between review emotions and product type when affecting sales. So, a multiple linear regression model involving all the constructed variables becomes practically promising for this study. Also, we would like to conduct ANOVA analysis to confirm the effects of the different aspects of products and related reviews on sales. Before we report the empirical results of above analyses, data is summarized as follows.

First, our results show that consumers use different content to address their evaluations on different products. As shown in Figure 3 (left), when consumers were evaluating search products, they often used: 1) good, 2) pretty, 3) delicious, and 4) cheap to emphasize their experiences. As shown in Figure 3 (right), when consumers were evaluating experience products, they frequently mentioned: 1) authentic, 2) good, 3) classic, 4) satisfied, and 5) happy to express their feelings.

The emotions extracted from product reviews (search vs. experience) in a subset (as previously discussed) are analyzed. The emotions in comparison include: 1) *Hateful* (*Mean* = 2.51 vs. 1.85, $p < .001$), 2) *Anxious* (*Mean* = 3.30 vs. 2.10, $p < .001$), 3) *Regretful* (*Mean* = 0.44 vs. 0.74, $p < .05$), 4) *Angry* (*Mean* = 0.69 vs. 0.38, $p < .01$), 5) *Happy* (*Mean* = 8.59 vs. 26.85, $p < .001$), 6) *Trustful* (*Mean* = 16.59 vs. 5.38, $p < .001$), and 7) *Wishful* (*Mean* = 6.03 vs. 2.21, $p < .001$), for search products and experience products, respectively. The results are shown in Figure 4.

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Search **Experience**

Figure 3. Word cloud of consumers' reviews on search vs. experience products

Several findings should be addressed here. Firstly, consumers were less likely to express their feeling Regretful and Angry, compared to other emotions. Secondly, consumers were more likely to experience a wide range of emotions when evaluating search products than experience products, except Regretful and Happy. Thirdly, consumers were more likely to present positive feelings than negative feelings in reviews on both search products (*Mean* = 10.40 vs. 1.73, p < .001) and experience products (*Mean* = 11.48 vs. 1.27, p < .001). Here, to collapse emotions' frequencies given different number of positive versus negative emotions, we use the average frequency in each group for comparison.

These findings suggest that we should differentiate search products and experience products in our analysis. Also, the results indicate that not all emotions are equal, as positive emotions are more frequently addressed, so review emotions should be tested as multiple independent variables in our model.

For regression analysis, we have considered several alternative models. Indeed, since we are interested in the effects of review emotions on sales, we could use a model that includes emotions as independent variables and sales as dependent variable, called *Model 1*. In the meantime, we would like to test a model that also includes product type as independent variable, called *Model 2*. Then, based on literature and the empirical results reported above, we would like to propose a model to treat product type as a moderating variable, called *Model 3*. The intention to propose and test these different models is simply to find the best supported explanation regarding the relationships among review emotions, product type, and sales.

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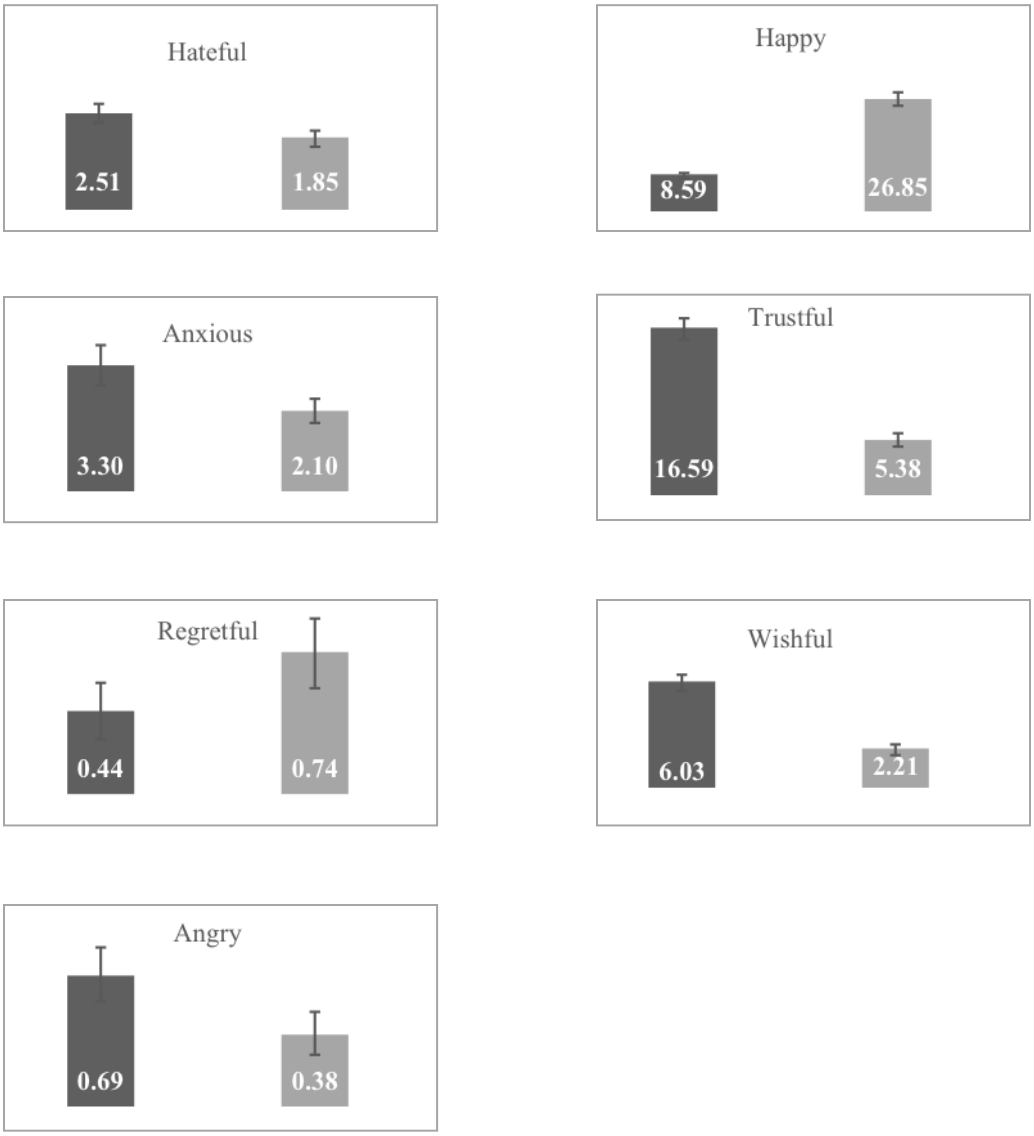
Search vs. Experience **Search vs. Experience**



Negative Emotions **Positive Emotions**

Figure 4. Review-embedded emotions for search vs. experience products

Table 6 presents the regression results. In *Model 1*, we have found that only feeling Happy positively affects sales, while other emotions are insignificant. In *Model 2*, results indicate that only Trustful positively affects sales, and Product Type is also significant. Specifically, experience products have significantly more sales than search products (*Mean* = 342.60 vs. 148.10, $p < .001$). In *Model 3*, as we consider product type a moderator, we have found that Trustful and Wishful both positively affect sales. Also, Wishful and Regretful interact with Product Type to affect sales. Similarly, in *Model 3* Product Type shows significant effect on sales.

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Variable	Model 1	Model 2	Model 3	Model 4
Hateful	-4.11 (2.35)	-1.67 (2.34)	-3.49 (3.03)	
Anxious	1.19 (1.69)	.07 (1.65)	1.81 (2.22)	
Regretful	-.99 (4.01)	-3.31 (3.91)	7.16 (5.49)	6.14 (5.40)
Angry	3.03 (5.88)	10.22 (5.92)	2.99 (8.16)	
Happy	3.27 (.47) ***	.87 (.72)	-.51 (1.46)	
Trustful	.49 (.44)	1.78 (.52) ***	1.34 (.61) *	1.32 (.58) *
Wishful	.10 (1.18)	2.30 (1.25)	4.06 (1.44) **	
Product Type		317.76 (73.93) ***	295.28 (109.67) **	240.34 (67.55) ***
Hateful × Product			6.49 (4.80)	
Anxious × Product			-1.17 (3.83)	
Regretful × Product			-20.05 (9.13) *	-17.01 (7.41) *
Angry × Product			5.79 (13.19)	
Happy × Product			1.18 (1.72)	
Trustful × Product			1.54 (1.28)	2.67 (1.05) *
Wishful × Product			-6.49 (2.98) *	
R^2	.18	.23	.26	.24

Table 6. Estimating the impacts of review emotions and product type on product sales (n = 259)

Also, we are concerned about the sizeable correlations between emotions, such as Happy and Trustful, potentially causing a multicollinearity problem. Therefore, based on correlation analysis we have attempted to reduce some highly correlated emotions from *Model 3*, resulting in a modified model – *Model 4*. To clarify, we have observed that Happy and Trustful are correlated while Trustful performs more stably in *Model 2* and *Model 3*, so Happy has been eliminated. This strategy has also been implemented to remove Wishful. In addition, to enhance model effectiveness we have simplified *Model 3* to be *Model 4* by ruling out insignificant variables. Finally, in *Model 4* there are two emotions remained, Trustful and Regretful, along with Product Type, as being the independent variables in *Model 4*. Obviously, *Model 4* is simpler and robust, indicating a good fit ($p < .001$, $R^2 = .24$).

To interpret our results, we have further conducted two-way ANOVA to demonstrate the main effects of emotions and the interaction effects of emotions and product type on sales. *Model 4* suggests that *Trustful* by itself affects sales, but also interacts with *Product Type* when affecting sales. Consistently, as shown in Figure 5, reviews containing feeling of *Trustful* would increase sales for both search products and experience products. But, for search products the effect of *Trustful* expressed in reviews would be even stronger. By contrast, feeling of *Regretful* does not affect the sales of experience products, but it affects the sales of search products as shown in Figure 6. Yet, we are not able to explain why reviews addressing more *Regretful* feeling would increase sales, which is contrary to our expectation.

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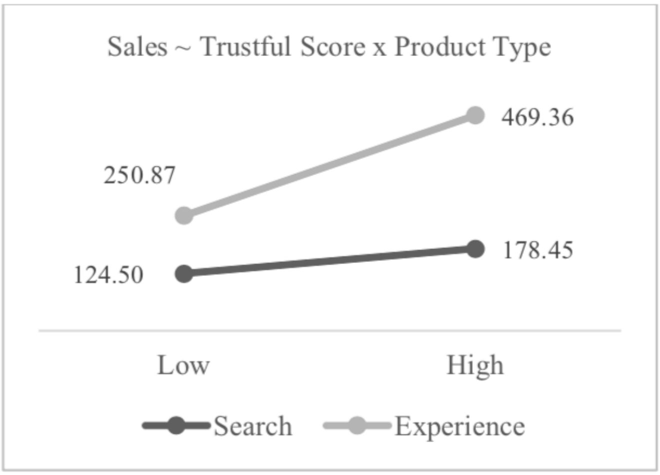

Figure 5. Feeling of trustful contained in reviews affects sales (n = 259)

Figure 6. Feeling of regretful contained in reviews affects sales (n = 259)

Our results partially support ***H1*** and ***H2***, indicating that some positive (e.g., *Trustful*) and negative emotions (e.g., *Regretful*) would affect product sales as expected. According to regression results, we could not state with certainty that negative emotions are more influential on sales than positive emotions. So, ***H3*** is not supported. Moreover, the effect of negative emotions (e.g., *Regretful*) on sales of experience product is not significant and therefore unable to support ***H4***. As shown in Figure 5, the effect of positive emotions (e.g., *Trustful*) is found to be stronger for experience products than search products, supporting ***H5***.

6. DISCUSSION

In this study, we provide empirical evidence to better understand the impact of review-embedded emotions and product type on sales. This work extends previous research that has mainly focused on review content, by addressing the important role of review emotions in enhancing review effort. In particular, the results indicate that

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emotions could affect sales, and these effects tend to be different for search product versus experience product. In addition, our results suggest that not all review-contained emotions would matter to firms and sellers striving to improve sales. As evidenced in our analysis, *Trustful* and *Regretful* feelings expressed in reviews would be more likely to drive sales, and therefore worth more consideration.

Theoretically, as past research tends to be more focused on the textual content of reviews but leave emotional review content underexplored, our study contributes to the current understanding of the relationships between review emotions and sales. By addressing sales as a target variable, our analyses specify the economic impact of generating and disseminating consumer reviews. Consequently, online review platforms and sellers would collect insights from this study and utilize emotional review content to guide consumers' purchase. In particular, our results would not support negativity bias as being widely recognized in research. Hence, e-commerce practitioners should play equally considerable attention to positive emotions (e.g., *Trustful*), which could positively affect sales. Also, we haven't found results supportive of past findings, regarding the strong effects of *Anxiety* and *Anger* (Yin et al., 2017). A possible explanation is that, past research examines the effects on perceived review helpfulness, not necessarily related to sales. The results would suggest review providers to share certain emotions, in order to be persuasive to peers. Review users would be better informed in decision making if they utilize both textual information and emotional content of reviews.

To address our limitations and provide directions for future research, we would like to state that: 1) our sample is relatively small, so we should collect more data to obtain solid results, 2) different social media could be examined to explore the difference across platforms, and 3) content analysis could be further conducted to make a better prediction of sales.

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