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AIS Transactions on Human-Computer Interaction

Volume 8 | Issue 3 Article 1

9-30-2016

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Yuan, L., & Dennis, A. (2016). The Happiness Premium: The Impact of Emotion on Individuals' Willingness to Pay in Online Auctions. *AIS Transactions on Human-Computer Interaction, 8*(3), 74-87. Retrieved from https://aisel.aisnet.org/thci/vol8/iss3/1
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Transactions on
Human – Computer Interaction

Research Paper

The Happiness Premium: The Impact of Emotion on Individuals' Willingness to Pay in Online Auctions

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Abstract:

Much research across various disciplines has studied individuals' bidding behavior in online auctions. Emotion is an important factor affecting individual behavior, but we know little about its effects in online auctions. We conducted a lab experiment to investigate the impact of positive emotion on individuals' willingness to pay in online auctions. We found that individuals with positive emotions bid more than those with neutral emotions; that is, they paid a "happiness premium" of about 10 percent. The effect size was medium (Cohen's d = 0.51). This study contributes to electronic commerce literature by identifying emotion as an important factor affecting online auction behavior. The findings also provide guidance to auction website design: websites can increase bid amounts by inducing positive emotions in potential customers.

Keywords: Emotion, Online Auction, Willingness to Pay, Electronic Commerce, Interface Design, Happiness

1 Introduction

Online auctions have been one of the greatest successes in electronic commerce. eBay, the largest online auction website, has more than 100 million active users worldwide. According to Forbes, in 2012, more than 75 billion dollars' worth of products were traded on eBay, and this number will double over the next six to seven years (Trefis Team, 2013). The fragmented market structure for online auctions has low barriers to entry, so many online auction sites exist; eBay accounted for only 11 percent of the industry's revenue in 2012 (Kaczanowska, 2012). Market researchers predict that the online auction industry will continue to grow and become more competitive in the future (Seo, 2013). Thus, understanding consumers' bidding behaviors in online auctions is an important topic for IS researchers.

Researchers have identified several factors affecting consumers' bidding decisions, including the number of visual cues (e.g., product pictures), product reviews (Li & Hitt, 2008), the number of bidders, and previous purchase satisfaction (Ariely & Simonson, 2003; Stern & Stafford, 2006; Yen & Lu, 2008). Much research studying online auction behaviors and bidding decisions has focused on rational choice models of behavior (Coleman & Fararo, 1993; Xiao, 2013). Yet, auctions, especially consumer-to-consumer auctions, are often an emotional process (Smith, 1990), so the consumer's emotional state may influence his or her perceived value of the product.

In this study, we investigate how an individual's emotions influence his or her willingness to pay for a product in an online auction. Specifically, we investigate the difference of impact between happy emotions and neutral emotions on individuals' willingness to pay. We conducted a lab experiment using an artificial auction website. Individuals who were happy were willing to pay a significantly higher price than individuals who were in a neutral emotional state.

2 Theoretical Background

2.1 Electronic Auctions and Bidding Behavior

Consumers have been gaining more and more pricing power, especially in the online environment with the rise of electronic businesses incorporating dynamic pricing mechanisms, such as online auctions. In this environment, understanding consumers' willingness to pay has become key to business success (Adomavicius & Gupta, 2005; Baker, Lin, Marn, & Zawada, 2001; Bapna, Goes, & Gupta, 2003; Hinz, Hann, & Spann, 2011).

Consumers' willingness to pay reflects their perceived value of the product (Uzawa, 1960). Prior research has examined many factors affecting consumers' perceived value of the product and their ensuing bidding behavior (Goes, Karuga, & Tripathi, 2010). Much prior research is based on rational choice theory, which assumes that an individual acts rationally to balance costs against benefits to maximize personal advantage (Coleman & Fararo, 1993; Runtian, 1999; Scott, 2000). Researchers have found factors such as product information, product image, pricing strategy, and system design to influence consumers' willingness to pay and bidding behavior. Researchers have also examined the effect of product reviews on price and have suggested separating perceived value from perceived quality as a strategy to control impact of product review (Li & Hitt, 2010).

Prior research has also found that increasing the quality of an auction business's e-image increases the prices received at the auction and consumers' willingness to transact with the business (Gregg & Walczak, 2008). Research has found that product specialization has explanatory power for reverse auctions. However, research has also found that non-contractible elements (including non-contractibility quality, supplier technological investments, information exchange, information diffusion, responsiveness, trust, and flexibility, of inter-organizational relationships) also have great explanatory power for reverse auctions (Ba, Whinston, & Zhang, 2003; Bapna, Jank, & Shmueli, 2008; Ho, Bodoff, & Tam, 2011; Li, Hess, & Valacich, 2006, 2008; Lim, Sia, Lee, & Benbasat, 2006; Mithas, Jones, & Mitchell, 2008; Webster & Martocchio, 1992). Research has also found implementing information feedback to an auction system to increase the amount of successful trading on the auction websites because it helps build trust, which is critical in electronic auctions (Adomavicius, Curley, Gupta, & Sanyal, 2013; Adomavicius & Gupta, 2005; Ba et al., 2003; Bapna et al., 2003).

Most of the research on electronic auctions has built on theories of rational choice. Behaviors resulting from or influenced by other factors, such as emotion, have not received much research attention. We believe that non-rational component remains a "missing piece" in our understanding of online bidding behavior. More understanding of this missing component can provide new insights and new findings that we can apply to designing online auctions. Emotion is one of the most important non-rational factors affecting behavior (Bechara, 2004; Toda, 1980).

2.2 Emotion

Emotion, as one type of affect, has a clear trigger and a short but intense effect (Frijda, 1994). Emotion is a subjective feeling related to personal needs, goals, or concerns towards the self or others and is typically triggered by events or objects in one's environment rather than internal factors. Once the stimulus, perceptions, or other triggers are no longer active, the emotion will gradually disappear. Emotion is often highly contagious and can spread through expression, vocalization, posture, and movements (Hatfield, Cacioppo, & Rapson, 1993; Schoenewolf, 1990).

Emotion, especially positive emotion, has been well studied in social psychology and marketing. Multiple social psychology theories emphasize the effect of emotion. According to construal level theory (CLT), positive emotion can increase individuals' willingness to think about abstract and future goals, while negative emotion makes people focus more on immediate and proximal concerns (Bar-Anan, Liberman, & Trope, 2006; Brief, Burke, George, Robinson, & Webster, 1988; Eyal, Liberman, Trope, & Walther, 2004; Fujita, Trope, Liberman, & Levin-Sagi, 2006; Labroo & Patrick, 2009; Liberman & Trope, 1998). Research on the impact of positive emotion has found conflicting results. Previous research in marketing has found that positive emotion can increase individual's resistance to temptation compared with neutral emotion (Fedorikhin & Patrick, 2010). Yet, research in the context of electronic commerce has found perceived enjoyment to increase consumers' impulse buying (Parboteeah, Valacich, & Wells, 2009). Individuals are more likely to be influenced by emotion during the formation of the first evaluations (Qiu & Yeung, 2008), which is often the case in online auctions.

We argue that emotion will influence the bidding decision in two ways. First, research has also shown positive emotion to have a strong impact to cause action (Frijda, 1994; Qiu & Yeung, 2008). Individuals with positive emotion will evaluate a product more quickly and impulsively than those with other emotions (Parboteeah et al., 2009; Qiu & Yeung, 2008). The more extreme the positive emotion, the greater this effect. Thus, when using an online auction website with sufficient product information and contextual cues, individuals with positive emotion will take less time to make a bidding decision than those with neutral emotion. Since they make the bidding decision more quickly, their bidding price reflects their initial perceived value of the product. Therefore, positive emotion is an important factor affecting bidding price by anchoring individuals more firmly on their initial impressions of a price to bid.

Second, according to the broaden-and-build theory of positive emotions, positive emotion usually induces individuals to have a higher self-evaluation compared with when they are in other emotional states (Fredrickson, 1998, 2001; Schwarz & Clore, 1983). Thus, individuals with positive emotion tend to have a higher evaluation of themselves compared with individuals with neutral emotion. Research refers to this process as over-valuation.

Individuals' often project their self-evaluation to external objects in their environment (Hirshleifer & Shumway, 2003; Loewenstein & Lerner, 2003). In the online auction context, the target bidding product serves as an ideal external object on which to project this self-evaluation and, thus, to have this phenomenon of over-valuation play out. Because bidders focus on the product they want to purchase, individuals will project their self-value on these products. Thus, people with positive emotion should perceive a product to have a higher value compared with those with neutral emotion. The perceived value of the product is the amount an individual is willing to pay for the product. In an online auction where consumers put their own bids, the willingness to pay is instantiated as the bid amount placed by the individual for that product.

Researchers usually categorize emotion as positive, neutral, or negative. However, individuals with mild positive emotion can exhibit different behavior from those with extremely positive emotion (Brief, Butcher, & Roberson, 1995; Federmeier, Kirson, Moreno, & Kutas, 2001; Mitchell & Phillips, 2007; Roehm & Roehm, 2005). Individuals with mild positive emotion often engage more in trying a diversity of products (variety seeking behavior) than those with neutral or extreme positive emotion (Menon & Kahn, 1995; Roehm & Roehm, 2005). Most prior research has categorized emotions into positive, negative, and neutral emotions and compared the impacts of these three distinctive conditions. However, some researchers argue that one should not treat mildly positive emotion the same as extremely positive emotion in all circumstances (Diener & Seligman, 2002; Teasdale & Fogarty, 1979) (Kahn & Isen, 1993; Roehm &

Roehm, 2005). To examine the impact of emotion in online auctions, we separated mildly positive emotion from very positive emotion to further distinguish their potentially different impacts.

We are aware of no prior research that has investigated the effects of positive emotion on bidding behavior. One related study examined the effects of emotion of the selection of bakery products (e.g., pies, pastries) and found emotion influenced which food individuals selected, but this study did not examine the effects on product valuation or willingness to pay (Qiu & Yeung, 2008).

Therefore, based on the theoretical arguments above, we theorize that individuals with positive emotions will value products higher than those with neutral emotions, which we will observe in the bidding price they place on the product. Therefore, we hypothesize that individuals with positive emotion (both mildly happy and very happy) will bid more for products than those with neutral emotion.

Hypothesis 1: Individuals with mildly positive emotion bid more for a product than individuals with neutral emotion.

Hypothesis 2: Individuals with very positive emotion bid more for a product than individuals with neutral emotion.

3 Method

3.1 Participants

Two hundred and eighty-two undergraduate students taking an introductory business course at a large U.S. public university participated in the lab experiment. We randomly assigned participants to one of the two treatments: neutral or positive. All participants received extra credit for participating in the experiment. Because we focused on neutral or happy emotions, we excluded 19 participants failed our manipulation check (i.e., they reported having negative emotion) from the analysis. We believe that the negative emotion triggers different cognition processes and mechanisms than positive emotion does in online auctions. Having participants with negative emotion in the sample would compromise our goal to understand the behavioral impact and decision making of positive emotion. We also removed another 14 participants who failed the manipulation check (described below) from the analysis. As such, our final sample comprised 249 participants.

3.2 Task

The task asked participants to imagine themselves as new students in a new masters-level program in the business school called the Master of Science in Graphic Design. In order to take courses in this new program, students needed to purchase two products, a camera and a laptop, from the bidding website provided in the experiment. The task instructions provided some detailed configuration requirements for each product.

For each product category (cameras or laptops), the participants had eight products to choose from. The eight products comprised two top-performing products, two low-performing ones, and four good-performing ones. All products in the same category had the same color and appearance to avoid the effect of appearance on participants' bidding choice. We presented participants with product descriptions, brand descriptions, rating reports, detailed test results, and suggested list price for each product. We adapted product descriptions and brand descriptions from Amazon.com. We adapted rating reports and detailed test results from Consumer Reports. Participants had to bid on one and only one product from each category. The bidding price could be either lower or higher than the suggested list price.

3.3 Treatment

There were two treatments in this experiment: positive and neutral. Participants in both treatments watched two video clips. The first video clip for both treatments was a three-minute car chase scene from The Bourne Legacy. The car chase scene is fast paced and highly arousing. It serves to attract the participants' attention to the manipulation. The second video for the positive manipulation was a 13-minute clip from the American's Funniest Video—Animal Extravaganza. The second video for the neutral manipulation was an eight-minute introductory database lecture.

Individuals have different levels of sensitivity to emotional stimuli (McLellan & McKinlay, 2013; Rotshtein, Malach, Hadar, Graif, & Hendler, 2001), so not all participants will have exactly the same emotional response to the two treatment videos. Instead of using the experimental treatments as the independent variable, we used self-reported emotion as the criterion to assign individuals to three different groups for analysis: neutral emotion group, mildly happy group, and very happy group. Assigning these individuals to three different groups was particularly important for the neutral treatment because it was less likely to materially change a participant's emotion. Those arriving in a positive or negative mood would likely carry those moods into the task and, thus, confound the results (i.e., if we used the treatment as the independent variable in the analysis, then individuals in a positive emotional state as they began the experiment and who were assigned to the neutral treatment would likely carry that positive emotion into the bidding task and would be misclassified in the analysis).

We administered the eight-item brief mood introspection scale (BMIS) (Mayer & Gaschke, 1988), which asks respondents to what extent they feel certain emotions presented as single words. The items use a four-point scale: 1 represents "definitely not feel", 2 represents "do not feel", 3 represents "slightly feel", and 4 represents "definitely feel". We used two items from this scale: "happy" and "lively" because these two items are directly related to positive emotion.

A third item asked about overall emotion, which we also drew from the BMIS scale (Mayer & Gaschke, 1988). We measured overall emotion using a 1 to 11 scale: 1 represented "extremely unpleasant", 6 represented "neither unpleasant nor pleasant", and 11 represented "extremely pleasant". We excluded participants who reported being unhappy (1-4 on this scale) (all from the neutral video treatment) from the study and removed from the analysis for failure to be in neutral or happy emotional states.

Because we used two different scales to measure the emotion status (two questions on a four-point scale and one question on an 11-point scale), we calculated z-scores of all the items to convert them to a common scale. The reliability of the three measures (after z-score transformation) using Cronbach's Alpha was 0.83, which showed adequate reliability. We averaged the z-scores of the three items as the measurement of individual emotion level.

Based on the averaged z-score, we categorized participants into three groups: the neutral emotion group, the mildly happy group, and the very happy group. We used a threshold of 25 percent of the average z-score as the criteria for dividing groups. We categorized participants with an average emotion z-score in the upper 25 percent (75%-100%) of all the participants into the very happy group. We categorized participants with an average emotional z-score the lower 25% (0-25%) into the neutral group. We categorized participants with an average z-score on emotion valence between 25 and 75 percent (i.e., the middle 50%) into the mildly happy group. There were 49 participants in the neutral group, 140 participants in the mildly happy group, and 60 participants in the very happy group. We found no theoretical foundation for our choosing 25 percent as our threshold, but we had to use some threshold and we believe a 25 percent threshold is a reasonable choice. As a robustness check, we also conducted the analysis (see Section 4) using a categorization groups based on a 20 percent threshold (20-60-20) and obtained the same statistical conclusions.

3.3.1 Dependent Variables

We calculated participants' willingness to pay as the percentage of the participant's bid amount to the suggested list price of the product he or she selected, which controlled for the effects of the different products' list prices on the bidding price. The list price of laptops ranged from US$480 to US$1150. The suggested list price of cameras ranged from US$700 to US$1999.

3.3.2 Procedure

When participants arrived at the laboratory, we instructed them to read the brief shopping task description. Then, we asked participants four questions regarding the content of the task: 1) the name of the master program, 2) how many product categories they had to bid on, 3) the names of these product categories, and 4) how many products they needed to bid on. We considered participants who failed to correctly answer those questions as not understanding the task and excluded them from the analysis. Next, participants in both treatment groups watched two video clips and evaluated the quality of the videos (to disguise the reason for the video clips). After watching the treatment videos, all the participants completed a questionnaire asking them to self-report their emotion level. Then, we directed participants to the online auction website on which they bid on one product from each of the two product categories. In the end, participants filled in a post-experiment survey containing demographic questions.

4 Results

We began with a manipulation check to compare the self-reported emotion between the two video treatments. The mean self-reported emotion of participants in the neutral video treatment was significantly lower than the mean emotion of those in the positive video treatment (F (1, 281) = 12.710, p = 0.000). This result suggests that the self-reported emotion measure was valid in capturing participants' emotions.

We used a repeated-measures GLM to examine differences among the neutral group, mildly happy group, and very happy group because the subjects bid on two products. Table 1 presents the data analysis results.

Table 1. Means, Standard Deviations, and Results of Statistical Analyses

Measure	n	Neutral		Mildly happy		Very happy		F	p-value
		Mean	Std.	Mean	Std.	Mean	Std.		
Bid amount as percent of list price	249	0.852	0.185	0.930	0.122	0.929	0.298	3.227	.039

The results indicate a significant effect of emotion on individuals' bids. Willingness to pay was statistically significantly different among the three emotion groups (F (2, 246) = 3.227, p = 0.039). Specifically, the mean of the bid amount as a percent of the suggested list price among neutral, mildly happy, and very happy groups was significantly different.

The order of products in which participants placed their bid did not affect their willingness to pay (F (1, 246) = 0.042, p =0.838). The Wilks' lambda value for the interaction between product type (camera or laptop) and emotion group was also not statistically significant (F (1, 246) = 0.993, p = .424), indicating there was no interaction effects between these two factors on individual's willingness to pay. Figure 1 compares the willingness to pay for products across the three emotion groups.

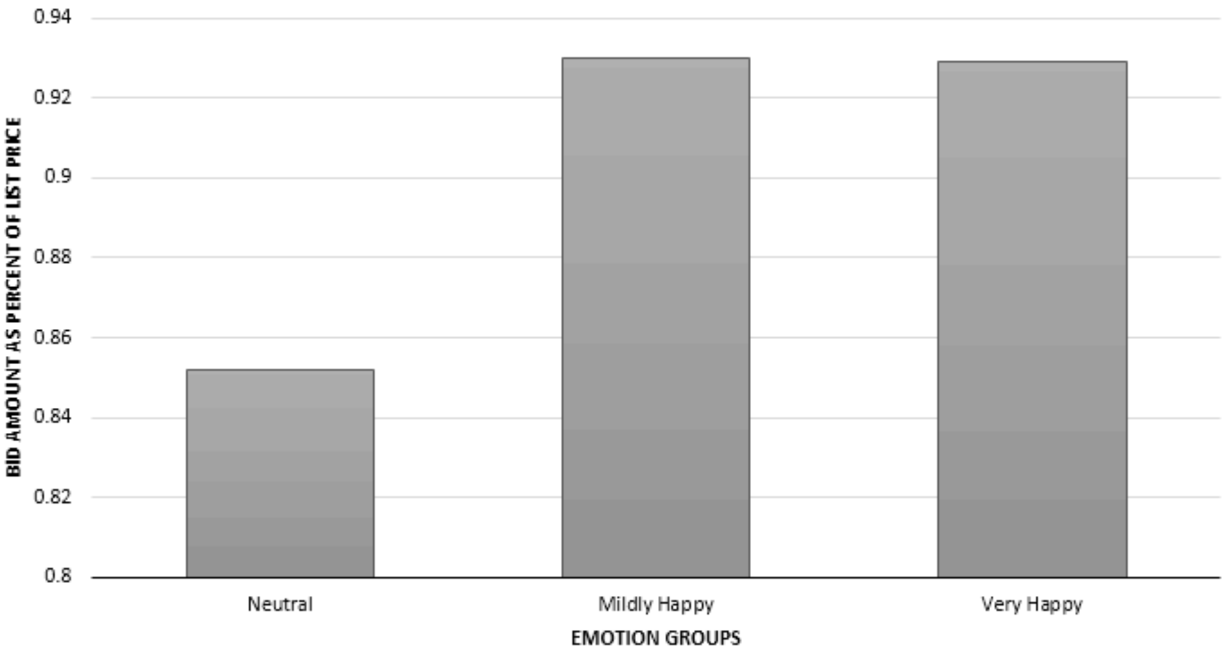

Figure 1. Mean Plots of Neutral, Mildly Happy, and Very Happy Groups

We conducted a post hoc analysis to compare the individuals' willingness to pay among the three groups. Table 2 presents the post hoc analysis results using Fisher's least significant difference (LSD). As the table shows, individuals' willingness to pay (the bid amount as a percent of list price) was significantly different between the neutral group and the mildly happy group (M = -0.079, SD = 0.032, p = 0.014) at the 0.05 level. Specifically, participants in the mildly happy emotion group bid significantly higher (93% of the suggested list price) compared to those in the neutral emotion group (85%). The effect size, calculated as Cohen's *d*, is in the medium range (Cohen's *d* = .51). Thus, our results support H1 (people with mildly happy emotion pay more than people with neutral emotion).

The willingness to pay was also significantly different between the neutral group and the very happy group (M = -0.078, SD = 0.037, p = 0.036). Similarly, participants in the very happy emotion group bid higher (93% of the suggested list price) compared to those in the neutral emotion group (85%). Thus, our results support H2 (very happy people pay more than people with neutral emotion). The effect size was in the small range (Cohen's *d* = 0.32) and, although the mean for this group was similar to the mean for the mildly happy group, the standard deviation was higher, which led to a different effect size.

There was no statistically significant difference in the willingness to pay between the mildly happy group and the very happy group.

Table 2. Post Hoc Multiple Comparison Results

Dependent variable	Mean (group I)	Mean (group J)	Mean difference (I-J)	Sig.
Bid amount as percent of list price	0.852 (Neutral)	0.930 (Mildly happy)	-.079	.014
Factor 2	0.852 (Neutral)	0.929 (Very happy)	-.078	.036
Factor 3	0.930 (Mildly happy)	0.929 (Very happy)	.001	.983

5 Discussion

Our study provides evidence that emotion affects individuals' bids in online auctions. Individuals with happy emotions, both mildly happy and very happy emotions, bid more than those with neutral emotions. We call this the "happiness premium".

The willingness to pay of participants with mildly happy or very happy emotions was almost 10 percent higher than that of the participants with neutral emotions (.93 versus .85). This difference is not only significant but meaningful. Cohen's d, a typical measure of effect size, is considered "medium" if is .5 or greater. The partial eta squared was .026— above the threshold of the large effect (.25). Thus, emotion has a significant and meaningful influence on online bidding behavior.

We believe positive emotion influences individuals' online bidding behavior by altering the perceived value of the product. Positive emotion is usually positively related with self-evaluation (Aspinwall & Taylor, 1993; Trope & Neter, 1994). The higher valuation of the self induces an increase in the perceived value of objects in the environment (Hirshleifer & Shumway, 2003; Loewenstein & Lerner, 2003) such that individuals with positive emotion tend to have a higher (or even biased) bids in the online auction.

In this study, we did not find any difference between the impact of mildly positive emotion and that of very happy emotion on individual's willingness to pay in the online auction context. Our findings are not parallel with the findings on individuals' variety seeking behavior (Menon & Kahn, 1995), which indicates that bidding in online auctions may be different in some ways from other forms of shopping.

Our findings provide further evidence that emotion can influence human behavior. The lens of emotion in individual behavior and decision making have not been deeply studied in online auctions or in some other areas of information systems research. We believe that these results have important implications for research and practice.

5.1 Implications for Research

We believe this study opens a new door in online auction research and electronic commerce research in general. Prior studies have examined "rational" factors affecting individuals' willingness to pay under the assumption of rational choice theory that individuals make rational decisions to optimize personal profit by maximizing gaining and/or minimizing cost. These factors are important. However, we need to look beyond the straightjacket of rational choice (Ho, 2006; Ho & Kwok, 2002; Tam & Ho, 2006).

The impact of emotion on decision making has been debated for decades. A neuroscience study found that emotion is an important factor in (or a precondition for) individuals' rational decision making (Bechara & Damasio, 2005). Our study contributes to theory in that we found that individual emotion can have a significant and meaningful effect on an individual's bidding behavior in online auctions. We believe we need more research on the impact of emotion on bidding behaviors and other online behaviors, including e-commerce. .

We focused on the impact of positive emotion on individuals' willingness to pay in online auctions. We did not study the impact of negative emotion. The underlying cognitive processes and mechanisms in online auctions triggered by negative emotion may be similar to or different from those triggered by positive emotion. We need research examining the effects of negative emotion on bidding behavior.

Our findings focus on the online auction context. However, we believe that we should expand the impact of emotion should to other forms of e-commerce. Compared with other electronic commerce channels, online auctions have their own characteristics. Online auctions are a dynamic pricing model in which the consumer's willingness to pay is directly translated into a bid amount. This model gives consumers more "power" in the transaction. Instead of making a buy or not-buy purchase decision for a product with a preset price (a categorical decision), consumers using online auction sites must develop their own bid amount (a continuous decision). A bidding decision may be different from a buy or not-buy purchase decision in terms of memory and cognition resources (Stafford & Stern, 2002). Therefore, we need future research to investigate the impact of emotion on individuals' behavior in other forms of e-commerce that use a buy-or-not-buy model may have different characteristics than online auctions with a dynamic pricing model.

Besides emotions, many other "non-rational" factors may affect individual decision making and behavior in online auctions and e-commerce more generally. We hope this study spurs researchers who are interested in understanding individual behavior and decision making under uncertainty in the context of electronic commerce to examine the effects of other "non-rational" factors of interest.

5.2 Implications for Practice

This study has three implications for practice. First, it provides guidance for practitioners on designing interfaces for online auctions. Happy consumers are more likely to bid higher for products. The designers of online auction websites such as eBay (and perhaps other electronic commerce websites) should explicitly consider designing their websites to increase positive emotion. By doing so, consumers are likely to pay more for products and, thus, increase website companies' revenue.

Second, companies and individuals selling products on online auction sites should customize the information about their products presented to consumers to trigger customers' emotions. Deliberately including text and images designed to induce positive emotion will likely result in higher bids and greater revenue.

Third, our findings have implications for consumers using online auctions. Consumers should recognize that they are likely to place a higher bid on the same product when they are in a happy mood than when they are in a neutral mood. Thus, if consumers attempt to purchase products rationally and avoid non-rational bidding behavior, such as over-price bidding, they should try to maintain a neutral emotion and avoid being happy, even mildly happy, while shopping on online auctions.

6 Conclusion

Many studies have focused on online auction behavior. Researchers have conducted most of these studies under the umbrella of rational choice theory. We focused on the impact of one "non-rational" factor, positive emotion, on individuals' willingness to pay. The results suggest that different levels of positive emotion have a similar effect on individual's bidding behavior. Both individuals with mildly positive emotion and those with very positive emotion bid significantly more than individuals with neutral emotion. The results of this study show many opportunities for future research on exploring the impact of emotion in online bidding and e-commerce. Online auction and other electronic commerce websites can use the results of this study to increase consumers' willingness to pay by increasing their positive emotions.

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