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The power of emotions in online decision making: A study of seller reputation using fMRI

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ABSTRACT

Online auctions use a variety of unique tools to provide quality signals for products and sellers in an attempt to overcome the online marketplace's limitations. These tools include feedback ratings and symbols that indicate reputation. However, surprisingly few studies have investigated the effects of reputation indicators in the decision-making process in online marketplaces. No prior study in our knowledge has examined the role of graphics indicators in online decision-making. We investigated the decision process and the price premium an individual was willing to pay for a product using an experiment with the Becker-DeGroot-Marschak procedure and event-related measures of brain activity. As signaling theory expects, results showed that the price premium paid for a product was higher when the product sold by a seller appeared with a high-reputation symbol. High-reputation seller indicators triggered significantly higher neural activity compared with low-reputation seller indicators in brain regions associated with emotions in the prefrontal cortex (the ventromedial prefrontal cortex). The degree of integrated cognitive value and cognitive and emotional value as represented by neural activity in the dorsolateral prefrontal cortex and VMPFC respectively was correlated with the price premium individuals bid for products. The results indicate the applicability of semeiotic theory along with signaling theory in the e-marketplace context and suggest fruitful avenues for further research.

1. Introduction

Online auctions use a variety of novel tools to provide quality signals for products and sellers in an attempt to overcome the online marketplace's limitations. These tools include product pictures and indicators that indicate sellers' reputation, such as feedback-rating systems [38]. Many studies have shown a positive relationship between seller-reputation indicators and the price premium that individuals pay for goods [see 62]. Both business-to-business and business-to-consumer e-commerce is proliferating, with online sales in China passing US $44.41 billion in 2017 [45]. As such, knowing how features for seller reputation influence decision making and outcomes in online markets has significant implications in e-commerce.

Most studies on reputation systems have investigated numerical ratings; few have investigated the effects of graphic representation indicators such as Taobao's hearts/diamonds/crowns grading system and eBay's star indicators.[1] However, evidence suggests that merchants believe that the graphic indicator ratings are important. For instance, Fan et al. [22] report evidence that merchants actively manage their reputation on Taobao by lowering prices to boost the volume to reach a higher seller grade. Some crown-reputation sellers even emphasize their crown-grade quality in their products' titles to attract buyers' attention (e.g., a “five-crown USB”), as well as adding five crowns indicators in product pictures.

Further, most studies on reputation systems have investigated the behavior of the market as a whole using archival data; few have investigated individual buyers' decision processes and how they react (which includes their emotional responses) to reputation indicators. Considering decision making at the individual level provides an opportunity to obtain greater insight into how consumers perceive reputation indicators and the outcomes of design decisions regarding their form.

Thus, in this study, taking into account decision processes represented by brain activity, we investigated the effects of seller-

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[1] Both eBay and Taobao are prominent online marketplaces. As of March 2016, Alexa rankings showed Taobao was ranked 12th in the world and eBay 23rd in terms of traffic (see www.alexa.com).

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reputation indicators on the price premium individuals were willing to pay for a product in an online market.

New decision-making theories argue that decision-making involves emotional processing apart from cognitive processing [15,34]. These theories see that biases and emotional processes (both conscious and unconscious) affect decision-making. In particular, the somatic marker hypothesis (SMH) [3,15,16] provides a well-supported account of how brain activity represents a potential choice's value as it relates to prior emotions and experiences, influences decisions. Several other studies from neuroscience discipline also show the involvement of emotional processing in the choice and decision-making processes (e.g., [11,39]).

This study makes significant contributions to theory and practice. On a theoretical front, it provides new theoretical insights into individual's decision making in online markets based on signaling theory, the theory of semiotics, and the somatic marker hypothesis by discussing the role of cognitive and emotional responses. On a practical front, it shows the impact of reputation indicators on the price individuals bid for goods and suggests that the designers of e-marketplaces should pay more attention to the indicators and their position on websites that they use.

The paper proceeds as follows. In Section 2, we present our theoretical background and hypotheses. In Section 3, we present our research method and our results in Section 4. Finally, in Section 5, we conclude the paper and discuss its implications and limitations.

2. Theoretical background

2.1. Signaling theory and seller-reputation indicators

Signaling theory in information economics offers a robust explanation for how individuals make judgments about product quality and decide on a price in a range of situations, particularly in the context of asymmetric information [7,8,12,43,54,56]. Signals are a seller's observable actions that credibly relay information about unobservable qualities of a product or seller to consumers [36]. Without a direct inspection, online shoppers cannot observe products' quality before purchasing them, and therefore, they use various signals to evaluate them [52].

Seller reputation has been argued to be a useful signal to help buyers infer a product's quality in traditional marketplaces [10]. Seller reputation can indicate the quality of products sold in previous periods and, therefore, often serves as a signal of the quality of products sold during the current period. In online marketplaces, seller reputation has been argued to signal sellers' fulfillment capabilities, such as timeliness of delivery and accurate description of products [23]. Additionally, online shoppers use seller reputation indicators as signals to infer that reputable sellers are less likely to default or deliver counterfeit copies [32].

A large number of studies have investigated the effects of seller-reputation indicators on economic outcome variables in e-commerce, such as price premium [5,23,41], auction price, or transaction price [30,46] or sales [58,61]. A price premium occurs when customers pay more for what they think will be a high-quality item because it comes from a high-reputation seller as compared to a low reputation seller [e.g., see 1]. Ye et al. [62] review the impact of seller reputation indicators and provide a representative sample of these studies. Seller-reputation indicators include numerical feedback scores such as total rating scores, positive and negative rating scores [5,46], percentage of the positive score [61], and textual reviews [23,60].

2.2. Graphic indicators as signals

Graphic indicators are being used as seller reputation indicators in online marketplaces. Ware [59] discusses the semiotics of graphic indicators and offers guidelines for using them. According to semiotic theory, graphic indicators can be divided into two types of indicators: sensory and arbitrary. Sensory indicators do not require learning: for example, the buyer understands that a picture of a camera represents a camera. Sensory indicators have immediacy—they are hardwired and easy to be recognized. On the other hand, arbitrary indicators depend on a learned understanding. For example, a high seller reputation indicator would signal the capacity of the seller that it is trustworthy, does not sell counterfeit copies, and delivers products on time [39,42]. A low seller reputation indicator would signal that the seller may not be that trustworthy and that the products sold by the seller may not be of high quality.

In other words, an arbitrary indicator can represent attributes related to seller reputation and convey signals that will facilitate online shoppers' decision-making. For example, the users of Taobao[2] (one of the world's largest online marketplaces) understand its graphic indicators of seller reputation (e.g., hearts, diamonds, and crowns) [22]. Online shoppers, when coming across an indicator of golden crowns (i.e., high reputation indicators), know that the indicator represents many attributes of the seller, such as trustworthiness, delivering products on time, and quality of its products [22]. Appendix A provides a review of relevant studies that have investigated the impact of seller reputation indicators on economic outcomes variables.

Accordingly, this discussion leads to our first hypothesis. Prior research has demonstrated a strong link between seller-reputation indicators and price premiums (see Appendix A). Taobao's seller-reputation indicators are examples of reputation indicators, albeit ones that researchers have not much studied and we expect them to influence price premiums. Such graphic indicators are arbitrary in the sense that one has to learn them; however, in e-marketplaces, users generally easily do so [22]. Thus, we hypothesize:

H1. The mean price premium for a product is significantly higher for a high-reputation seller indicator compared with the mean price premium for a low-reputation seller indicator.

2.3. Decision making processes and neural activity

In this study, we investigate the process and outcomes of the influence of seller-reputation indicators on the consumers' decision to pay for a product. We do so by gathering data from event-related neural activity in an experimental setting. To use the neural data, we need to make assumptions about what the activity in a specific area of the brain means in terms of human psychological processes [20]. Making these assumptions, however, involves difficulties.

The problem is one of reverse inference. As Dimoka et al. [20] note, one cannot infer a one-to-one map activation in one brain area with one psychological process (p. 402). Instead, more than one process may activate one brain area, and one process may activate several different brain areas [49]. To counter these difficulties, we rely on several strategies, namely: (i) region-of-interest (ROI) analysis suggested by Poldrack [49] and Glymour and Hanson [24]; (ii). matching a “psychological description” with patterns of tasks, stimuli, and observed networks of activation over a variety of tasks until one can reliably infer some correspondence between psychological description and network (see Glymour and Hanson [24]); (iii) considering the effects of anatomical damage on the psychological processes that a human can perform. If damage to a brain area interferes with specific processes, then one can argue that the brain area is needed for that process.

Several brain regions are involved in the processing of cognitive and emotional responses related to stimulus evaluation and decision-

[2] The Taobao system has 21 grades representing different levels of cumulative numerical ratings; a hierarchical system of hearts, diamonds, blue crowns, and golden crowns represent these numerical ratings from low to high. The lowest grade is no rating (and, thus, no indicator) (score $<$ 4) and the highest grade is five golden crowns (score $>$ 10,000,001).

making. However, we investigate only the regions of the ventromedial prefrontal cortex (VMPFC) and the dorsolateral prefrontal cortex (DLPFC). This approach is consistent with prior research on consumer neuroscience related to the computation of decision value [35,48,57]. Other brain regions such as the medial orbitofrontal cortex, anterior cingulate cortex, insula, and ventral temporal cortex are associated with both positive and negative affect [39]. Given the limitations of available techniques, we could not differentiate between the activation of these regions for high-reputation indicators and low-reputation indicators.

2.4. Integrated cognitive and emotional value in decision-making and VMPFC

The neuroscientist Antonio Damasio [15] proposed the somatic marker hypothesis (SMH) that suggests that emotions play a role in decision-making. He draws evidence for this hypothesis from several case studies of patients with damage to specific brain regions in VMPFC.

In brief, the SMH proposes that decision-making deficits following VMPFC damage arising from an inability to use emotion-based signals from the body ("somatic markers") when considering different response options. The somatic markers serve to indicate the value of what one considers based on links to prior emotions and experiences. The accompanying cognitive processes may be conscious or unconscious [3]. Research supports many of the SMH's assumptions. For example, Zajonc [63] has famously concluded: "preference needs no inference." His work showed that individuals exhibited preferences for some stimuli after previous exposure to them, although the individuals were not consciously aware that they had seen them. Dunn et al. [21], in a review, conclude that reasonable evidence exists to support the model's aspect concerning the neural correlates of decision-making and emotions.

The SMH [3,15] provides a base for describing brain areas of interest in human reasoning, decision-making, and the involvement of emotions in the decision-making process.

Prior work has found VMPFC activation to be associated with integrated subjective value [48] and value computation [57]. In general, researchers have found that VMPFC activation is associated with positive affect [40], attractiveness [53], preference [44], and decision-making [35]. Damasio [15] argues that VMPFC activation is associated with both reasoning and emotions.

In addition, meta-analyses help arrive at psychological descriptions corresponding to neural activity in brain regions. For example, Clitheroe and Rangel [11] found that VMPFC plays a vital role in the decision-making process. Particularly, they found that VMPFC "…integrates relevant information from a variety of networks (of the brain)" and was involved in "… computing stimulus value whenever such variables are needed, regardless of the phase of the decision task" (p. 1299). Based on the above discussion, we refer to VMPFC activation in a decision-making process as "integrated cognitive and emotional value."

Prior research on seller reputation indicators has shown that when participants provide a high rating for a product or seller, they usually associate positive emotions with that rating [40,62]. On the contrary, when they provide a low rating for a product or a seller, they associate negative emotions with that rating [62].

Thus, we believe that online shoppers will experience positive affect for high reputation indicators leading to high levels of integrated cognitive and emotional value (i.e., a high level of VMPFC activation). However, for low reputation indicators, online shoppers will experience less positive affect leading to low levels of integrated cognitive and emotional value. In a bidding process in an online auction, the presentation of graphic reputation indicators pre-bid and at bidding should stimulate both cognitive and emotional processes. Hence, we hypothesize;

H2a. At the time of pre-bid, the cognitive and emotional values (i.e., the activation of VMPFC) for high-reputation seller indicators are significantly different from those for low-reputation seller indicators.

H2b. At the time of bidding, the cognitive and emotional values (i.e., the activation of VMPFC) for high-reputation seller indicators are significantly different from those for low-reputation seller indicators.

Following O'Doherty's [42] definition, we define VMPFC as including the medial orbitofrontal cortex (mOFC) and the adjacent ventral medial cortex (VMC) (see also [9,26,48]).

2.5. Cognitive value in decision-making and DLPFC

A second area of the brain, DLPFC, is also related to decision-making, as it is involved in cognitive processing related to decision-making [20,31,48]. However, unlike VMPFC, this area is not related to emotional processing [40]. As with VMPFC, DLPFC should be associated with seller reputation indicators, but differently [57].

Building upon semiotic theory [59], seller reputation indicators (i.e., graphic indicators) are arbitrary - when online shoppers come across graphic indicators of seller reputation, they associate those indicators with the several attributes that they represent such as seller's trustworthiness, quality of products, and timeliness of the delivery [35,39,42]. When individuals are presented with a graphic indicator for seller reputation, they engage in cognitive processing to interpret what the symbol means. Thus, DLPFC should be activated.

However, unlike the case with VMPFC, DLPFC is not associated with emotions, so there is not necessarily a difference at the item-group level between the amounts of cognitive processing a high-value indicator stimulates and the amount a low-value indicator stimulates. Both types of indicators could stimulate, on average, over a group of items, much the same degree of activation for an individual. As there is not a strong argument here, we do not formally present a hypothesis. However, we did analyze the differences between conditions of high and low reputation indicators for DLPFC at the item-group level and found no significant differences (see Appendix B).

At the individual item level, the degree of cognitive processing that is activated in DLPFC should be more sensitive to the degree of interest and value associated with that item for the individual. If they are more interested in purchasing an item, they bid a higher value for it and think harder about it beforehand. This argument leads to hypotheses H4a and H4b below.

2.6. Price premium effects

As discussed in the preceding sections, the levels of individuals' integrated cognitive and emotional value (the activation of VMPFC) and cognitive value (the activation of DLPFC) should indicate how much individuals value a product in a transaction and, thus, influence the price premium an individual is willing to pay for a product, as shown in the next two hypotheses.

H3a. At the time of pre-bid, an individual's cognitive and emotional value (i.e., the activation of VMPFC) will be positively associated with the price premium the individual is willing to pay for the product.

H3b. At the time of bidding, an individual's cognitive and emotional value (i.e., the activation of VMPFC) will be positively associated with the price premium the individual is willing to pay for the product.

H4a. At the time of pre-bid, an individual's cognitive value (i.e., the activation of DLPFC) will be positively associated with the price premium the individual is willing to pay for the product.

H4b. At the time of bidding, an individual's cognitive value (i.e., the activation of DLPFC) will be positively associated with the price premium the individual is willing to pay for the product.

3. Research method

3.1. Participants

Sixteen university students participated in our experiment (7 females and 9 males; mean age = 21.75, SD = 2.206). The students were all enrolled at a large university in South-Eastern China, and all had Mandarin Chinese as a first language. We excluded one additional participant from data analysis because of technical problems. All participants were right-handed, healthy, and had a normal or corrected-to-normal vision. They had no history of psychiatric diagnoses or neurological or metabolic illnesses and were not taking medications that could interfere with the fMRI assessment. All participants had online purchase experience (mean = 4 years, SD = 1.461) with at least ten successful transactions on Taobao.com. Participants provided written consent before participating in the formal experiment. The review board of the relevant university approved the experiment.

3.2. Design and materials

We used a 2 × 1 within-participant factorial experimental design (seller reputation: high versus low). Participants attended two BDM auctions with 100 trials in each auction. One BDM auction was an online auction without any seller information. The second was an online auction with sellers differing in reputation for the same product.

3.2.1. Stimuli

We selected real-life products and sellers and used indicators of two grades of sellers on Taobao that differed in perceived reputation. We used five crown indicators and five heart indicators to proxy high-reputation and low-reputation sellers respectively. We chose 100 branded products (e.g., a USB driver) based on a pretest. The average retail price of the products was approximately 50 RMB (approximately US$8). However, we set the distribution of bidding prices in the experiment from 0 to 30 RMB. Each participant received an endowment of 30 RMB to place bids. This arrangement meant that participants could purchase an item at a discounted price and they could bid a higher price if they really wanted to buy the item.

We presented all the stimuli using color pictures with a resolution of 72dpi. We controlled the stimuli presentation and response recording with the software E-prime (Psychology Software Tools, INC.). On average, the total duration for each individual trial was 18 s (Fig. 1).

3.2.2. Procedure

The experiment had three stages: pre-scanning (pre-test questionnaire and first auction), fMRI scanning (second auction), and post-scanning (post-test questionnaire) (Fig. 2).

The purpose of using fMRI is to collect brain activity related to signal processing and decision-making in online auction context. The brain activity of regions called VMPFC and DLPFC was measured in particular. We informed participants that they would perform two online auction tasks. We provided detailed instructions before each auction began.

Before the first auction, each participant filled out a questionnaire on Internet usage experience and shopping experience on Taobao, which included average shopping frequency per month, the number of times they shopped, and total expenditure during the last three months. After completing the questionnaire, we gave participants 30 RMB to make bids in the BDM auctions. In the first auction, each participant saw the entire range of 100 products one at a time. In the second auction (scanning), each participant saw only the 50 products for which they had given the highest bidding prices in the first auction. Thus, they would not see any products in the second auction that they thought were undesirable to avoid any confounding effects of negative affect on the neural activation of the value system.

We used willingness-to-pay (WTP) as a measure of the value that individuals assigned to products when placing bids, which is congruent with other work in consumer neuroscience. Researchers have used the Becker-DeGroot-Marschak (BDM) procedure [6] to elicit an individual's WTP at the point of the decision [26,48]. According to the BDM procedure, a participant makes a bid for an item, and the item's market price is randomly drawn from the distribution of real market prices or a given range. If the bid is equal to or above the price, the participant receives the item and pays the drawn price. If the bid is below the price, the participant does not receive the item and pays nothing. The bids participants place generate real-time measures of the values assigned to an item- the higher the bid, the higher the item's value. The optimal strategy for participants is to bid precisely their expected value for each item. If they bid less, they diminish their chances of getting the product at a “good” price. If they bid more, they risk paying too much for an item. In the end, for each participant, we randomly selected one of the 200 auctions in which they had bid. They then received the product bid for that auction plus any remaining money. For example, if they bid RMB 20 for a USB drive (which had a market price less than or equal to the bidding price—say RMB 18), they got the USB at the market price plus any money remaining from their original endowment of RMB 30 (i.e., RMB12). Participants did not have to worry about spreading a budget over the different products, so they could treat each trial as if it was the only one. In this way, we could record how much participants valued a product in each trial, and the price premium a participant would like to pay for a product sold by a ranked seller.

3.2.3. fMRI experiment paradigm

The second auction with fMRI scanning comprised five runs with 20 trials each. In each run, we set half of the 20 trials to transact with a five-crown seller and half with a five-hearts seller presented in random order. Participants bid twice for each product in different runs—once with a five-crown seller and once with a five-hearts seller.

On each trial, participants first saw a fixation sign ‘+’ at the center of the screen for 2 s. They then saw a product for 4 s followed by another screen with the product and a reputation indicator for either a high- or a low-reputation seller, which also appeared for 4 s. The next screen had a beginning price added, which was the amount the individual bid in the first auction (WTPB). This screen remained until the participant pressed buttons. The participants needed to place a bid for the product as if they were transacting with the given seller. Participants confirmed a final price by pressing a button. We recorded the final price as missing data if participants did not press the confirm button within 2 s. After each bid, a black screen gave participants a break between trials for 4 to 8 s (mean = 6 s). We set this time interval according to related studies (e.g., [48]). On average, the total duration for each trial was 18 s.

3.3. Measures and manipulation

Table 1 summarizes the variables in the study and their measures. The independent variable was the seller reputation (either high or low). We obtained measures of neural activity in three ways. First, we used whole brain general linear model (GLM) analyses to localize the brain areas with statistically significant differences between experimental conditions. Second, we defined functional region of interests (ROI) based on prior related studies. We extracted the mean percentage change of BOLD signal of all voxels in each ROI for each condition and for each subject along the time course of each trial. We used these data as neural representations of psychological processes. Third, we extracted the percentage change of BOLD peak signal in each ROI when seller-reputation indicators appeared and when participants bid (with consideration for the delayed BOLD response of 4 to 8 s). The dependent variable was price premium (WTP_diff), which we measured as the difference between holistic WTP (HWTP) in the second auction and base WTP (WTP_B) in the first auction. In the first auction, participants saw the image of the product without the seller-reputation indicator. In the second auction (scanning), participants saw both the product- and seller-reputation indicator. The amount a participant bid on a transaction option (to buy a product from a given seller) served as a measure of “holistic” WTP, which we termed either $HWTP_H$ (for high-reputation sellers) or $HWTP_L$ (for

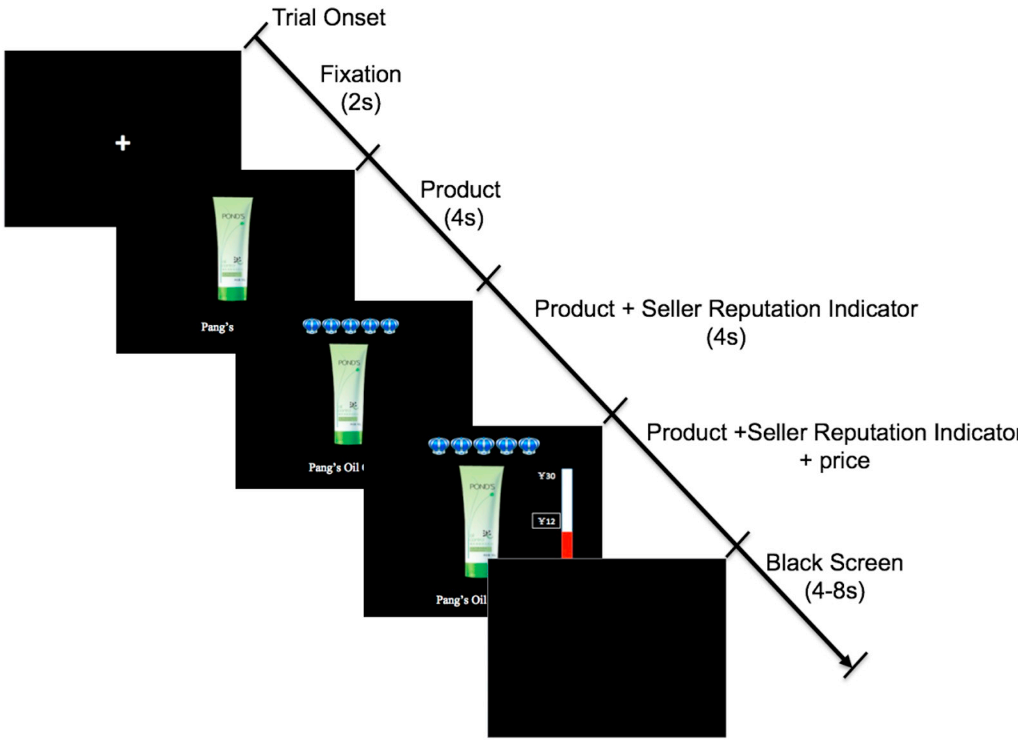

Fig. 1. Time structure of one trial in second auction including experimental stimuli.

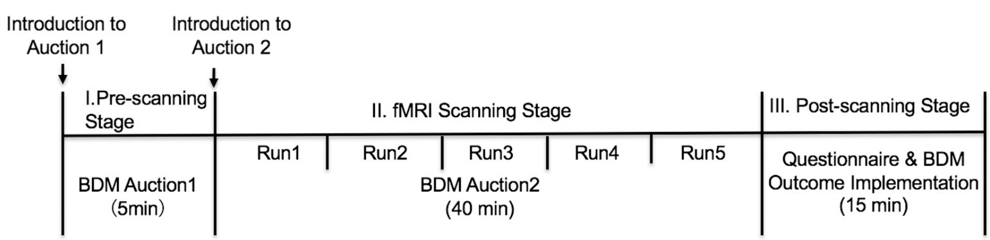

Fig. 2. Experimental procedure.

low-reputation sellers). The HWTP represents a subjective value reflecting the integrated value of both the net value of the product and the cognitive value of the seller's reputation.

3.4. Data analysis

We acquired the fMRI data on a GE 3 T MR750 scanner in five separate sessions of 8 min each. We collected data for HWTP and response time (RT)[3] with E-prime software. We initially used paired sample *t*-tests to examine the difference between the HWTP of high-reputation sellers and low-reputation sellers. For neural activity, we first analyzed the fMRI data with statistical parametric activation maps (SPMs 8), according to Dimoka's [18] guidelines. The overall analysis method is similar to that of Sokol-Hessner et al. [57]. We pre-processed raw data to remove noise, increase the signal-to-noise ratio, and prepare the data for further comparison. Second, we used a whole-brain general linear model (GLM) of blood-oxygen-level-dependent (BOLD) activity to localize the brain areas with statistically significant differences between the treatment conditions (i.e., high-reputation sellers versus low-reputation sellers) (for hypotheses H2a, and H2b). Third, we carried out a region of interest (ROI) analysis on VMPFC based on prior studies [40,48] (for hypotheses H3a and H3b). Finally, we used the more targeted data extracted from the ROIs to examine the correlation between brain activity and price premium (for hypotheses H3a, H3b, H4a, and H4b).

4. Results

4.1. Initial checks

We used statistical tests to investigate any possible confounding effect of presentation order on holistic WTP. We found no effects about runs. Responses to questions on perceived reputation in the post-scanning stage indicated that our manipulations were effective. High-reputation sellers received significantly higher scores on a perceived reputation scale (6.125, $SD = 0.540$) than low-reputation sellers (3.469, $SD = 1.048$) ($t = 9.092$, $p < 0.001$, $df = 15$).

4.2. Effect of seller reputation on price premium

Our first hypothesis concerns the price premium paid for high-reputation sellers. Table 2 shows that our data supports this hypothesis.

[3] We recorded response time from the onset of the "beginning price" presented on the screen to the time point when participants pressed the button to adjust the price. During this time period, participants decided how much to bid for the product. In this study, response time is the product evaluation time during which value computation occurs.

Table 1
Definitions and measurements of key variables.

Term	Description	Abbr.	Measurement
Seller reputation	Seller-reputation category	SR	1 = High-reputation seller (five crowns) 0 = Low-reputation seller (five hearts)
Willingness to pay (base)	Personal base value of product sold online	WTP_B	The bidding price a participant was willing to pay for a product in the first auction (RMB 0–30).
Holistic willingness to pay	Amount bid for a product sold by a seller	HWTP	The bidding price a participant was willing to pay for a product sold by a seller in the second auction (RMB0–30).
		$HWTP_L$	HWTP for a low-reputation seller
		$HWTP_H$	HWTP for a high-reputation seller
Price premium	Amount above the base WTP for a product sold by a seller	WTP_Diff	The difference between HWTP and WTP_B for a product bid for by an individual.
Integrated cognitive and emotional value	Neural representation of cognitive and emotional value of a product sold by a ranked seller, bid phases	–	Three indicators: (1) GLM1 (using BOLD signals) with all trials; (2) GLM2 (using BOLD signals) with contrast of high-reputation seller versus low-reputation seller trials; (3) Regions-of-interest (ROI) analysis
Cognitive value	Neural representation of cognitive value at time of pre-bid and biddings	–	Three indicators: (1) GLM1 (using BOLD signals) with all trials;(2) GLM2 (using BOLD signals) with contrast of high-reputation seller versus low-reputation seller trials; (3) Regions-of-interest (ROI) analysis

Table 2
Comparison between seller conditions.

Variables	High-reputation seller	Low-reputation seller	Independent *t*-test
Price premium (RMB)	0.708 (2.201)	−2.886 (3.172)	26.198***, df = 1585
$HWTP_{H/L}$ (RMB)	23.297 (4.539)	19.698 (4.492)	15.873***, df = 1585
Response time (ms)	1363.310 (657.276)	1258.000 (698.685)	3.093**, df = 1585

Note:
*** $p < 0.001$.
** $p < 0.01$.

The price premium (WTP_diff) was significantly higher for high-reputation sellers. In addition, holistic WTP was also significantly higher. In terms of magnitude, participants paid 16% more for products listed by high-reputation sellers than those by low-reputation sellers.

4.3. fMRI results

4.3.1. Cognitive and emotional value (i.e., the activation of VMPFC) comparisons with GLM

At the time of pre-bid, there was no significant difference between the activation of VMPFC for high-reputation seller indicators from those for low-reputation indicators (H2a not supported). However, H2b was supported - at the time of bidding, the difference between the activation of VMPFC for high-reputation seller indicators from those for low-reputation indicators was significant (SCV peak PFWE_corr = 0.003, peak z = 3.96 in MNI coordinate of (−5, 60, −1)) (see Fig. 3A). Please see Appendix C for a detailed discussion of MNI and SCV (see Appendix D for the meaning of terminology).

4.3.2. Integrated cognitive and emotional value (i.e., the activation of VMPFC) time courses with ROI

GLM is a method based on whole-brain normalization and voxel-level functional analysis. ROI analysis is based on region-level functional analysis, which offers finer localization and increased sensitivity to task-related effects than GLM. There exists significant activation in VMPFC when comparing high- and low-reputation seller trials. Hence, we applied ROI analysis on VMPFC to further explore the differences between the two conditions.

We extracted trial averaged time-course data from ROIs for each subject, which we averaged across subjects. The time courses (Fig. 4) shows that VMPFC activated significantly in high-reputation seller trials compared with low-reputation seller trials after participants began to place a bid (time = 14 s, $t = 3.484$, $p < 0.001$; time = 16 s, $t = 2.967$, $p < 0.01$) (H2b supported) but not at the time of pre-bid (H2a not supported).

4.3.3. Correlates of brain activation and price premium

We conducted a sensitive analysis at the individual level, within-subjects, to examine the correlations between brain activation and price premium (see Table 3). We extracted BOLD peak data in ROIs of VMPFC and DLPFC.

VMPFC activity at the bid point was positively related to price premium (H3b supported) but not at pre-bid (H3a not supported). However, the activation of DLPFC was positively associated with price premium at both pre-bid (H4a supported) and bidding (H4b supported). The results indicated that males significantly placed higher bids for products than females. Younger subjects placed significant higher bids than older ones.

5. Discussion

We investigated the effects of seller-reputation indicators on the price premium an individual was willing to pay for a product in an online market while considering brain activity related to decision-making processes and the role of emotions, particularly that of positive affect. The study's results supported all hypotheses except H2a and H3a – we did not find support for a statistically significant difference between high-reputation seller indicators and low-reputation indicators at the time of pre-bid or that the individual's integrated cognitive and emotional value at the time of pre-bid would be associated with a price premium. The findings provide only partial support for the SMH, as they show that emotions play a role in decision making at a point when individuals are about to make a decision and not necessarily at other stages of the decision-making, such as when individuals are exposed to seller-reputation indicators. Other research has also suggested the involvement of VMPFC at the time of decision-making (e.g., see [11,35]). However, we found that the activation of DLPFC was associated with price premium at the pre-bid level, which suggests that prior learning attached to the seller reputation indicators evokes cognitive processing as soon as users are exposed to the reputation indicators. Future research could further investigate the effects of reputation indicators at pre-bid stage.

5.1. Theoretical contributions

This research makes several theoretical contributions. First, the results support signaling theory in that we found reputation indicators influence price premiums, an outcome congruent with prior work. We extend prior work, however, in that the reputation indicators we used were graphic indicators rather than the numerical and verbal ratings previously studied. Second, in line with prior research (e.g.,

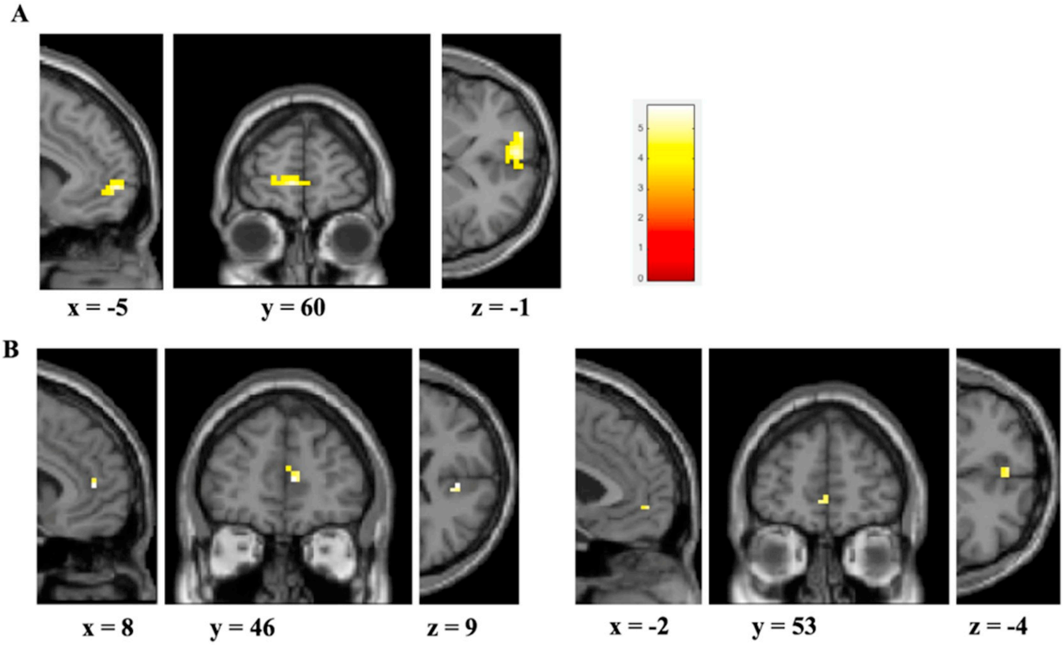

Fig. 3. Statistical maps for VMPFC of GLM2: A) coordinate of (−5, 60, −1) when seller indicator presented; B) coordinate of (8, 46, 9) and coordinate of (−2, 53, −4) when bidding.

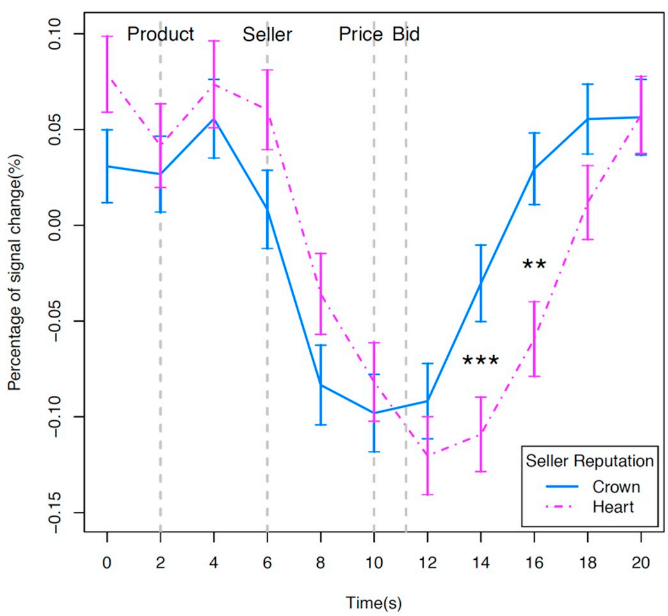

Fig. 4. Averaged time course (ROI) analysis for VMPFC.

[11,35,40]), we found that in the absence of detailed information when individuals have to rely on informational signals, both cognitive and emotional responses play a role in the decision making, particularly by engaging the brain region of VMPFC at a time when a decision is made.

Third, based on semiotic theory, we argued that seller-reputation indicators examined in this study were arbitrary and because they represent high and low ends of several attributes related to seller's reputation, their exposure would lead to significant cognitive processing in DLPFC region. The study's findings support this hypothesis as we found statistically significant associations between the activation of DLPFC and price premium, both at the time of pre-bid and bidding. This finding is significant and suggests that exposure to arbitrary seller-reputation indicators leads to cognitive processing in the DLPFC region due to prior learning – a finding congruent with prior work (e.g., [35]). Future research can further explore the potential of semiotic theory, particularly the role of different arbitrary indicators that represent seller reputation, such as stars in online purchase decision making.

Fourth, this study contributes to the NeuroIS research related to the stimulus presentation (e.g., see [25,50, 51]) because the findings of our research (H4a was supported) and prior research (e.g., [35]) suggest that the activity of DLPFC is of critical importance at the time of stimulus presentation.

Last, our study uses a neuroscience technique (i.e., fMRI) to investigate the decision process in the context of online marketplaces. Mostly, prior studies have used cross-sectional or archival methods to study individual decision processes and have treated neural correlates of the decision-making process as a black box. Our study opens up that black box and sheds light on the underlying neuronal activity and how that activity can be used to predict constructs important in IS research.

5.2. Practical contributions

The study shows the impact of reputation indicators on the price individuals bid for goods, something merchants have demonstrated they accept when they attempt to manipulate their rankings. Therefore, designers of e-marketplaces should pay more attention to the design and position of the seller-reputation indicators on websites. Are the indicators on eBay as prominent as on Taobao? Do consumers need more education in what the eBay indicators convey? eBay combines the selling and buying reputation for one merchant in its rating system, both in numerical scores and its stars system. Is this a good idea? Future research of the type performed here with neuroscience measures could help address these questions.

5.3. Potential limitations and directions for future research

We used an experimental approach and, thus, our study is subject to the limitations of experiments (in particular, sacrificing realism to the experimental design's constraints). However, the experiment provides insights into processes that are not available from other methods such as cross-sectional surveys and archival methods.

The study was based on Taobao, a website based in China, and had participants who were residents of China. We do not know to what degree the results would apply to a website in Western culture. Further, we do not know if one would find the effects we observed if the reputation indicators

Table 3
Correlations between VMPFC activation and price premium (N = 1578).

Variable	VMPFC_prebid	VMPFC_bid	DLPFC_prebid	DLPFC_bid	Gender	Age	Price premium
VMPFC_Prebid	1						
VMPFC_bid	0.430**	1					
DLPFC_prebid	0.556**	0.277**	1				
DLPFC_bid	0.205**	0.608**	0.418**	1			
Gender	0.038	−0.045	0.045	−0.062***	1		
Age	0.055***	−0.020	0.048	−0.031	0.015	1	
Price premium	0.093**	0.068**	0.106**	0.050***	0.086**	−0.070**	1

Note:
*** $p < 0.001$.
** $p < 0.01$ (1-tailed) (Pearson's r).

were other graphical indicators such as stars. Future research can investigate these issues. Future research can particularly investigate the effects of other reputation indicators such as stars at the pre-bid and bidding stages.

5.4. Concluding remarks

This study offers several important contributions. First, it shows the influence of reputation indicators, rather than numerical ratings or textual reviews in online markets, on prices and price premiums. Second, it provides new theoretical insights into individual decision making in online markets by providing evidence of the role of emotional responses along with cognitive responses. Third, it shows how one can employ neuroscience literature and techniques to investigate constructs necessary for decision-making. The study provides fruitful grounds for further research that informs theory and practice.

Authors' contribution

All authors contributed equally to this manuscript.

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Appendix A. Provides a review of relevant studies that have investigated the impact of seller reputation indicators on economic outcomes variables

Table A1
Studies of the impact of seller reputation.
(Adapted from [64].)

Relevant literature	Variable[a]	Product	Website	Method[b]	Effect[c]
Ba and Pavlou (2002)	Positive ratings, negative ratings	CD, Camera, DVD, Windows Server etc.	eBay	Field experiment	P
Canals-Cerda (2012)	Textual positive and negative feedback	Different types of Artwork	eBay	Archival	P
Chan et al. (2007)	Positive and negative ratings	Notebook	Not given	Archival	S (+/− rating)
Depken and Gregorius (2010)	Overall reputation score	iPhones	eBay	Archival	N/A
Dewan and Hsu, (2004)	Seller ratings	Stamps	ebay	Archival	P
Drake et al. (2015)	Reputation score	Product not mentioned	N/A	Survey	N/A
Du et al. (2012)	Feedback score	8 different product categories	EachNet.com	Archival	P
Elhadary (2014)	Seller's feedback	Gold items	eBay	Archival	P
Hong and Pavlou (2012)	Feedback rating	Services	www.freelancer.com	Archival	P
Hou (2007)	Seller ratings	LCD monitors	eBay	Archival	P
Houser and Wooders (2006)	1. Shades 2. Sellers ratings	Pentium 3 computers	eBay	Archival	P
Kauffman and Wood (2006)	Reputation score	Coins	eBay	Archival	P
Li et al. (2015)	Overall rating	Apparel	Taobao	Archival	S
Li et al. (2009)	Overall ratings	Paintings, silver plates	eBay	Archival	S
Luo and Chung (2010)	Overall rating score	200 different electronic products	BizRate.com	Archival	P
Melnik and Alm (2002)	Overall ratings	Coins	eBay	Archival	P
Pavlou and Dimoka (2006)	Feedback text comments	Electronic products (e.g., iPod, DVD, CD)	eBay	Archival	P
Resnik et al. (2006)	Number of positive feedback	Vintage postcards	eBay	Field experiment	S
Walia and Zahedi (2013)	Positive and negative rating	Motor products	eBay	Archival	P
Wang et al. (2015)	Guest rating	Hotel services	Expedia.com	Archival	P
Xu and Ye (2015)	Seller reputation (old vs new entrants)	Intel graphic card, RAM, IdeaPad	Taobao	Archival	P
Yao et al. (2014)	Seller rating	Memory chips, iPhone, Milk powder	Taobao	Archival	P, S
Ye et al. (2013a) [61]	Overall score, Feedback score (+/−)	Drinking vessels	eBay, Taobao	Archival	S
Ye et al. (2013b) [62]	Overall feedback score	Perfume, mobile refill & memory card	eBay, Taobao	Archival	S
Zhou and Hinz (2015)	Number of comments for a product	Food, clothing, jewel, books etc.	Taobao	Archival	S
Want and Teo (2001)	Seller's feedback rating	Coins	eBay	Archival	N/A

Notes:
[a] "Rating," "Overall reputation," "Overall rating," and "Seller's rating" mean total numeric score. "Shades" means an icon that shows if the seller has joined within the last 30 days or has changed his/her ID within 30 days.
[b] "Archival" means data obtained from the database(s) of transactions. "Experiment" means a controlled randomized experiment.
[c] Reputation Effect (P) = significant price and reputation correlation; S = significant reputation and sales volume correlation; NA = no significant correlation.

Appendix B. Brain images of cognitive value (i.e., the activation of DLPFC)

For DLPFC we did not hypothesize a difference between high and low reputation indicators at the item-condition level, as we believed in both conditions individuals would be engaged in cognitive processing to much the same extent. However, we did test for differences as a check on our understanding. Fig. B1 shows the statistical image results for GLM1.When the seller indicator was presented, we observed significant activation of the left DLPFC (Fig. B1A) at the threshold of $p < 0.001$ uncorrected and an extent threshold of 5 voxels which suggests that the region of DLPFC is involved in stimulus processing especially stimulus associated with prior learning (e.g., arbitrary seller-reputation indicators). With small volume correction (SVC), in peak level, $P_{FWE\_corr} = 0.000$, peak $z = 4.31$ in MNI coordinate of (−48, 20, 42). At the point of bidding, the area of right DLPFC (Fig. B1B) was significantly activated (SCV peak $P_{FWE\_corr} = 0.001$, peak $z = 4.14$ in MNI coordinate of (28, 40, 39); SCV peak $P_{FWE\_corr} = 0.007$, peak $z = 3.76$ in MNI coordinate of (21, 50, 32)). The GLM2 analysis showed no significantly different activation in DLPFC at the time of pre-bid and bidding when comparing high- and low-reputation seller indicators. These statistical image results indicate that both sides of DLPFC were involved in cognitive value computation.

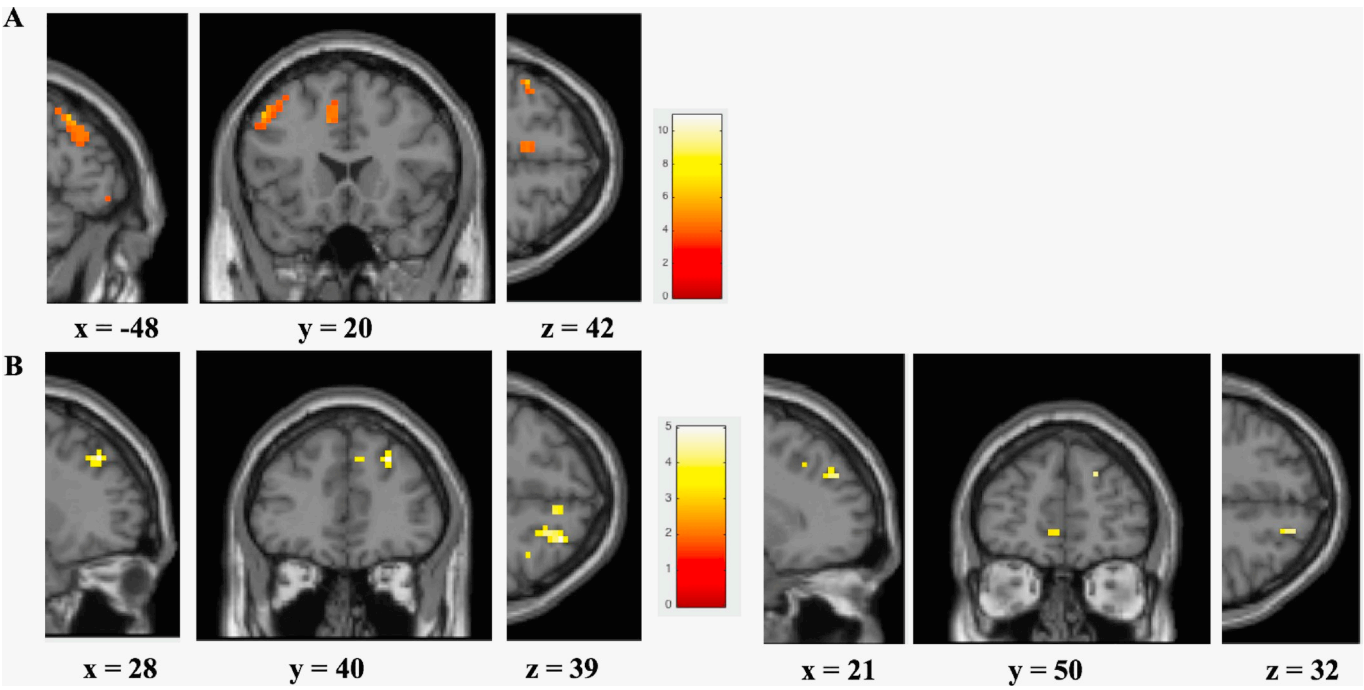

Fig. B1. Statistical maps for DLPFC of GLM1: A) coordinate of (−48, 20, 42) when seller indicator presented; B) coordinate of (28, 40, 39) coordinate of (21, 50, 32) when bidding.

Appendix C. Detailed discussion of MNI and SCV

To perform group studies using functional imaging data, the individual brain images are usually transformed into a common coordinate space. The two most widely used spaces in the neuroscience community are the Talairach space and the Montreal Neurological Institute (MNI) space. The Talairach brain is the brain dissected and photographed for the famous Talairach and Tournoux atlas. The atlas has Brodmann's areas labeled, albeit in a somewhat approximate way. To be more representative of the population, the MNI created a new template that was approximately matched to the Talairach brain in a two-stage procedure. First, they took 250 normal MRI scans and manually defined various landmarks and the edges of the brain. Each brain was scaled to match the landmarks to equivalent positions on the Talairach atlas. This resulted in the 250 atlas brain that is very rarely used. They then took an additional 55 images and registered them to the 250 atlas using an automatic linear registration method. They averaged the registered 55 brains with the 250 manually registered brains to create the MNI 305 atlas. The MNI 305 brain is made up of all right-handed subjects, (239 M, 66 F, age 23.4 ± 4.1). The MNI305 was the first MNI template. The International Consortium developed the current standard MNI template for Brain Mapping (ICBM). The ICBM152, which is the average of 152 normal MRI scans that have been matched to the MNI305 using a nine parameter affine transform, was adopted by SPM from version 99 on.

The GLM was analyzed the whole brain volume. When we have a priori hypothesis as to an area of expected activation in a statistical parametric map, we can correct the multiple comparisons among volumes in a specific region other than across the whole brain volumes. That is why we need a small volume correction (SVC).

Appendix D. Glossary of terminology (referred to as terms)

Table D1
Glossary of terminology (referred to as terms).

Terms	Meaning	Terms	Meaning
SCV	Small volume correction	SPAMs	Statistical parametric activation maps
VMPFC	Ventromedial prefrontal cortex	GLM	General linear model
DLPFC	Dorsal lateral prefrontal cortex	BOLD	Blood-oxygen-level dependent
mOFC	Medial orbitofrontal cortex	FWE	Family-wise error

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