Understanding Social Preference Effects in E-Commerce Using Behavioral and EEG Metrics

Fu-Yin Cherng
Dept. of Computer Science
UC Davis, CA, USA
fcherng@ucdavis.edu

Jingchao Fang
Dept. of Computer Science
UC Davis, CA, USA
jcfang@ucdavis.edu

Yinhao Jiang
Dept. of Computer Science
UC Davis, CA, USA
injiang@ucdavis.edu

Annie Lin
Dept. of Computer Science
UC Davis, CA, USA
aaalin@ucdavis.edu

Taejun Choi
Looxid Labs US Inc.
San Jose, CA, USA
taejun.choi@looxidlabs.com

Hao-Chuan Wang
Dept. of Computer Science
UC Davis, CA, USA
hciwang@ucdavis.edu

CHI'20,, April 25–30, 2020, Honolulu, HI, USA
ACM 978-1-4503-6819-3/20/04.
https://doi.org/10.1145/3334480.XXXXXXX

Abstract
Browsing and purchasing products in virtual reality (VR) become incrementally popular due to its immersive and realism experience, which also makes VR an ideal space for online shopping in the future. This work investigates individual preferences when viewing products in VR. Notably, we focus on the influences of displaying the collective preference from others on individual preferences. Besides measuring self-report preferences and behaviors, we applied a VR-embedded portable electroencephalogram (EEG) headset to acquire participants' cognitive states associated with subjective preferences in the experiment. Based on the results, we discussed the external and internal effects of social display and the design implications of how to design social information display for e-commerce systems in VR.

Author Keywords
Preference; electroencephalogram (EEG); brain-computer interface; social conformity.

CCS Concepts
•Human-centered computing → Human computer interaction (HCI);

Introduction
Understanding what people want and supporting what people need is at the core of e-commerce, product designs,

and service designs today. Social computing applications that generate personalized recommendations of information to users also depend on the capture and modeling of individual preference. In HCI and UX design, the community in general shares the view that user's perception of a system can be valuable data to consider when choosing between designs [14]. However, little is known about how individuals form preferences on aspects of design. Subjective user preference alone also appears to be insufficient to guide and support design changes [14].

Preference formation can involve internal (personal) and external (social) factors [17, 8, 20]. While preferences are clearly individual-based evaluations, the formation of preferences is not always independent of external influence. Social psychology research has shown that individual opinion and behavior can be shaped by social pressure (e.g., opinions of peers) and social conformity (opinions of higher status individuals or social majority groups) [5]. Social influence can also be internalized, affecting individual's evaluation when there's no social interaction or social presence. For example, studies have showed that individual's social orientation (individualism vs. collectivism) can still have an impact on crowd workers' ratings of products when performing the rating task individually online [18].

In e-commerce, user-generated ratings of products are commonly displayed to support consumer's decision making for purchasing. What's unclear is whether the social display of past users' ratings affects the current shopper's personal preference of products, and how different components of user evaluations, such as the distribution of ratings versus qualitative comments, change the ways individuals evaluate a product prior to using it. It is also important to investigate how strong is such social influence on changing individual's true preference or instead triggering strategic conformity behaviors.

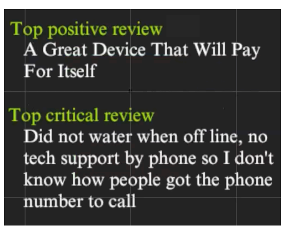
To address these questions, we present a laboratory study to investigate the effects of displaying user-generated ratings and comments on individual preference in a virtual shopping environment. We manipulated what types of collective evaluation to display when rating products, either a display consisting of both score distribution and qualitative comments (i.e., full display of social preference) or a display of only quantitative score distribution (i.e., limited display of social preference). We assessed how individuals evaluate the products, as reflected in their ratings, as well as behavioral and biometric data for capturing non-stated aspects of personal preferences. The results of our study aim to generate design implications to inform the design of e-commerce systems in VR environments, and to demonstrate a novel mixed-method research strategy that combines self-reports, behavioral and EEG brain-sensing data to support the research of individual preferences in HCI.

To capture individual preferences, stated preference is one widely practiced method of measurement [2]. Stated preference involves individuals to participate in self-report, independently recall or recognize information, and decide what they prefer among a set of options [13, 2, 11]. While stated preference is feasible to capture aspects of preference, it also has some important limitations in preference measurement due to the nature of subjective reporting. First, individuals may not be able to accurately report what they actually prefer when there's motivation to falsify such report (e.g., under the influence of social pressure). Second, stated preference may not be able to capture the continuous mental states when individuals change their behaviors and preference given an external intervention, but self-reports may only sample preferences prior or post to the shift.

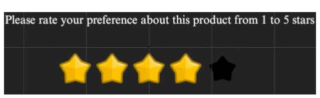
Recent works in brain-computer interface and HCI have

(a) Image and title of product

(b) Rating distribution of product



(c) Positive and negative reviews



(d) Preference rating

Figure 1: Screenshots of each page in the experiment.

been using Electroencephalography (EEG) brain-sensing techniques to complement behavior- and survey-based usability evaluations by offering information on individual cognitive states [4, 3]. EEG-based measures are less influenced by reporting biases and can provide data directly associated with different cognitive functions [21, 16]. As the formation of preference and social influence is known to involve multiple and complicated cognitive functions [5, 20], EEG-based measures can offer in-depth and more variant observations along with the conventional measures of preference. In our study, we used EEG data to understand users' cognitive responses throughout the process of preference formation when viewing and rating products unobtrusively and to connect individuals' stated preferences with inner-/neuro-preferences. We collected users' EEG data as concurrent physiological data of preference level. We evaluated whether the collected physiological data correlates with the level of preference stated by the participants.

Method

Experiment Design and Task

The experiment consists of two phases. In the first phase, we displayed a series of products with their landing image and title (see Figure 1a). The participants were asked to rate their preference for each product one by one on a 5-point scale, as shown in Figure 1d to collect participants' initial preferences of the products without any intervention. To compare the three display conditions, we implemented phase 2 of the study as a within-subject experiment. In the second phase, we designed three conditions – no-display, limited-display, and full-display condition – in which the participants would receive different information about products before they rated preference for the products. In the no-display condition, participants see the same product information as what they saw in the first phase. In the limited-display condition, after showing the product information, we showed the distribution of the online preference score for the product (see Figure 1b). Lastly, in the full-display condition, the titles of both most positive and negative reviews of the product were displayed in a separate view, followed by the rating distribution (see Figure 1c). After viewing the information from one of these three conditions, participants were also asked to rate their preference for the presented product. The order of conditions was counterbalanced, and the products rated in the first phase were randomly assigned to the three conditions and re-rated by participants.

Material Preparation

We sampled and crawled the images and user evaluations of 90 products under the category of "Smart Home Devices and Systems" from Amazon.com. For each product, we collected the landing image, title of the product, its average rating, and rating distribution, and also the comments (i.e., customer reviews). To reduce participants' burden of reading long reviews, we chose to collect the titles of top positive and negative reviews calculated by Amazon. To minimize the branding effect and individual difference, we crawled the new to smart home categories and manually removed unqualified products such as products with low resolution landing images, products with no reviews and ratings, and products with similar appearance but different names. The average of all products' mean rating is 3.63 with standard deviation of 0.61. The average price is $128.9 and 90% of products lay within the price range between $0 to $400.

Instruments and Measures

The experiment was conducted in a VR environment with HTC VIVE [7] head-mounted display (HMD). VR was simulated using a Windows 10 PC with an Intel CORE i9 and a GeForce RTX 2070S graphics card. The participants used the HTC VIVE controller to select the preference score dur-

Figure 2: The experiment setting.

Figure 3: HTC VIVE and built-in EEG sensors, Looxid Pro.

ing the experiment. For measuring EEG signal in prefrontal cortex, Looxid Pro [12] which is compatible with HTC VIVE was used (see Figure 3). From six dry flexible EEG electrodes, signal data in prefrontal cortex including AF3, AF4, Fp1 Fp2, AF7, AF8 channel followed by EEG 10-20 system were measured and collected. Reference EEG signal was collected from FPz at extended 10-20 system. Figure 2 shows a participant wear our device during the experiment.

Participants and Procedure

We recruited 30 participants (15 male and 15 female) with ages ranging from 20 to 29 years old. Nineteen participants reported that they have used Virtual Reality equipment before, and the remaining eleven participants stated it was their first time using VR. We invited the participants to our lab and instructed them about the purpose of our study. We introduced the equipment to participants after they signed a consent form. Participants were asked to sit on a fixed chair and put on HTC VIVE headset. To collect participants' EEG baseline, a calibration was at the beginning of each phase where they stared at the center of a fixed cross for five seconds. There is a 3-minute break between two phases when participants can take off the headset and take a rest. After the two phases ended, they completed a survey with questions of demographics and experience in using VR. The entire experiment lasted about 30 minutes and participants received a $10 Amazon gift card to compensate their time.

Data Recording and Processing

We collected participants' rating of each product and their reaction time of submitting the rating after the rating page was shown. The data points with a preference score of zero (i.e., no preference) were excluded. Then, we computed the changes in rating and reaction time by subtracting the rating and reaction time of the second phase by those of the first phase when rating the same product.

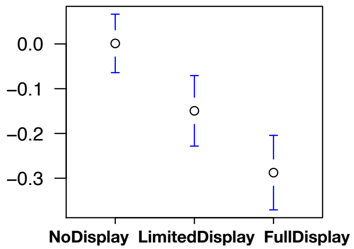
The EEG signal was recorded throughout the experiment at sampling rate of 500 Hz. Time synchronization between each event in the Unity application and EEG signal was done by Looxid Pro signal acquisition system. Recorded EEG signals were notch filtered at 60 Hz. Band-pass infinite impulse response filter in a range of 0.1 to 50 Hz was applied to EEG signals. The EEG data recorded in phase 2 was selected for further analysis. The epochs used for computing spectral power were 1200 ms long, starting 100 ms before and ending 1,000 ms after the stimulus onset. All epochs with voltage variations exceeding 180μV were rejected to remove artifacts such as DC bias, blinks, and slow eye movements [1]. According to the method in prior study [16], three frequency-based measures were extracted using Welch's spectral density estimation: frontal alpha asymmetry (indexing emotion and motivation) [6], alpha/theta power (indexing attention) [19, 16], and theta/gamma power (indexing memory processing) [10]. The final value of each measure was computed by averaging across all channels and time in each epoch.

Repeated-measures ANOVA were conducted on the behavioral and EEG data with applying random effect on participant ID. Tukey's method for multiple comparisons were applied in post-hoc tests.

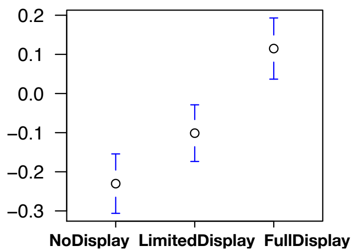
Results and Findings

Effects of Social Display

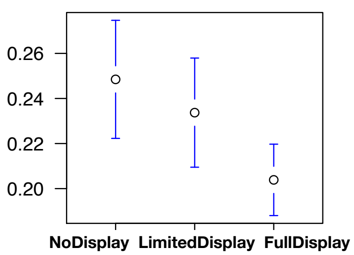
Figure 4a shows the comparison of the changes in preference score in different conditions. We found that the participants gave lower preference ratings to the products in the condition with the limited and full display ($F(2,2633)=14.32$, $p<.001$). Moreover, the preference score decreased more in the full-display condition than in the limited-display condition ($p<.05$). This result indicates that showing social information makes participant decrease their initial rating of the



(a) Change of preference score



(b) Change of reaction time (sec)



(c) Alpha/theta ratio (indexing attention)

Figure 4: The behavioral and EEG results in different conditions. The error bar represented 95% confidence interval.

preference to the same product. We considered this result might be due to the seeking of social confirmation so that the participants chose to give more conservative ratings. Although we showed both positive and negative reviews, the results that the full-display condition changed more negatively in preference score could indicate that showing the reviews additionally could enhance the effect of confirmatory. The other potential reason could be the negativity bias, in which the negative information has a more significant effect on human cognitive processes than neutral or positive information [15]. Hence, the negative review has a greater effect on the participants than the positive one, which resulted in lower preference scores in the full-display condition.

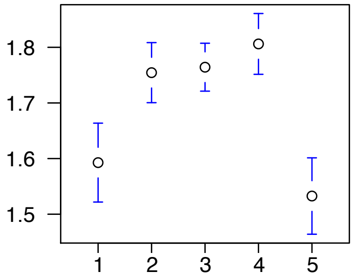
The condition also has main effect on the change of reaction time (F(2,2633)=22.55, p<.001). From Figure 4b, we can see that participants need more time to rate preference in the full-display condition. Since there is more information shown in the full-display condition, this result might imply that the participants need more time to process before making a decision when more information was shown. On the other hand, we can see that the reaction time of participants decreases in the no-display and limited-display conditions in which the decrease in the no-display condition is significantly greater than in the limited-display condition (p<.05). Since the participants rated the same 90 products in phase 2, this result reveals that the participants had become familiar with the task so that they need less time to rate the preference. However, the extra information shown in the full-display condition instead took participants more time to rate.

Besides the behavioral results which reveal how the social display affects the participants externally, we found that the alpha/theta ratio derived from EEG data is significantly different given the condition (F(2,618.06)=3.18, p<.05). As shown in Figure 4c, the alpha/theta ratio in the full-display condition is the lowest, which suggests that the participants engaged the highest level of attention and cognitive process in the full-display condition among all condition [19, 16]. This result could support the behavioral finding that full-display condition has the longest reaction time, since the information and review presented in the full-display condition required participants more mental resources to process than the other conditions.

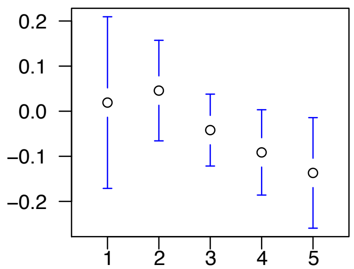
Effects of Preference

Besides the effect of the display condition, we also want to understand participants' behavioral and EEG responses when seeing and rating the products with different preference score. As we can see from Figure 5a that the preference score has main effect on reaction time (F(1,2682.5) = 29.18, p<.001). The reaction time of rating a product with scores 2 to 4 was longer than the reaction time of the scores 1 and 5 (p<.001). However, there is no significant difference between the reaction times of the scores 1 and 5. This result shows that the participants can make a quick decision when they have an extreme preference for products. However, since the products with the highest preference and lowest preference have a similar reaction time, it is still difficult to distinguish whether the participants like or dislike the products by reaction time alone.

For the EEG results, we found that preference score has a main effect on the frontal alpha asymmetry (F(1,392.95) = 5.36, p<.05). As shown in Figure 5b, the frontal alpha asymmetry decreases significantly with the increase of preference score. As the increase of the frontal alpha asymmetry has been proven to be associated with positive emotion and higher engagement, and vice versa [6], this result indicates that the participants indeed underwent a more emotionally positive process when viewing the products with



(a) Reaction time (sec)



(b) Frontal alpha asymmetry (indexing emotion and motivation)

Figure 5: Results in different preference scores across conditions.

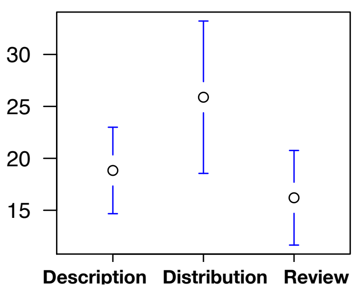


Figure 6: Theta/gamma ratio (indexing memory processing) in different views.

higher preference. Moreover, this result could suggest that frontal alpha asymmetry can be treated as an effective index to human inner preference.

Effects of View
Given the ability of EEG to monitor participants' cognitive state continuously and passively, we can assess the participants' cognitive states in the different steps in a trail, which allows us to decompose a trail and conduct more nuanced comparisons. Since the participants exposed to different views in our study, we would like to know whether the participants process these views differently. Figure 6 shows that the theta/gamma ratio is significantly different in different views (F(2, 377.71)=3.81, p<.05). The view of showing preference distribution has the highest theta/gamma ratio than the view of showing product information and reviews (p<.05). As the decrease of theta/gamma ratio is associated with the increasing activities related to memory encoding and recollection [10, 16], this result indicates that the view of product information and review evoked more activities of memory processing than the Distribution view. The potential reason might be that both view of showing product information and reviews contain more complex semantics (e.g., the title of products and the reviews) than the visualization of rating distribution, so the stronger memory-encoding activities were activated to process the information appeared in these views.

Design Implications and Future Work
According to social translucence, displaying opinions and activities to one another can stimulate participants, and facilitate collaboration [9]. However, our results show that the effects of displaying social information are not necessarily positive, especially in the scenario of involving preference construction. Although the condition of full social display engaged the participants the most, the participants also needed more time to decide their preference and even changed their preference more negatively in the full-display condition. In this way, the preference score the participants reported might not reflect their genuine preference for the products. Instead, the collected preference would mostly reflect the consequence of seeking social awareness and approval, which is not desirable since the customers want to obtain the evaluation of the product by looking at the preference score gave from others. Moreover, the effect of view reveals that different types of social information evoked different levels of cognitive activities, suggesting that the display form of social information should also be considered in the design process. For example, if a shopping site is designed for fast browsing, the designer would like to use the rating distribution to show others' opinions on the product to avoid engaging too many activities of memory encoding from users and save users processing time to determine the preference for the products.

The present work also demonstrated the benefits and potential of integrating EEG-based measures in the interdisciplinary study of social computing. EEG measures explained more variance and revealed the underlying psychological mechanisms associated with the behavioral results. Along with the results from conventional measures, we can derive a more comprehensive picture of the influences of interventions on users. The present work only reported the primary analysis of EEG data. We plan to conduct more analysis (e.g., temporal analysis) to uncover more cognitive responses related to the formation of preference and the effect of social conformity in the future. Besides, the study with the scenarios of online shopping utilizing more affordances in VR (e.g., interacting 3D models of products) will also be included in our future works.

REFERENCES

[1] Andrew CN Chen, Weijia Feng, Huixuan Zhao, Yanling Yin, and Peipei Wang. 2008. EEG default mode network in the human brain: spectral regional field powers. *Neuroimage* 41, 2 (2008), 561–574.

[2] Heidi Q Chen, Tomonori Honda, and Maria C Yang. 2013. Approaches for identifying consumer preferences for the design of technology products: a case study of residential solar panels. *Journal of Mechanical Design* 135, 6 (2013), 061007.

[3] Fu-Yin Cherng, Yi-Chen Lee, Jung-Tai King, and Wen-Chieh Lin. 2019. Measuring the Influences of Musical Parameters on Cognitive and Behavioral Responses to Audio Notifications Using EEG and Large-scale Online Studies. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. ACM, 409.

[4] Fu-Yin Cherng, Wen-Chieh Lin, Jung-Tai King, and Yi-Chen Lee. 2016. An EEG-based approach for evaluating graphic icons from the perspective of semantic distance. In *Proceedings of the 2016 CHI conference on human factors in computing systems*. ACM, 4378–4389.

[5] Robert B Cialdini and Noah J Goldstein. 2004. Social influence: Compliance and conformity. *Annu. Rev. Psychol.* 55 (2004), 591–621.

[6] James A Coan and John JB Allen. 2003. Frontal EEG asymmetry and the behavioral activation and inhibition systems. *Psychophysiology* 40, 1 (2003), 106–114.

[7] HTC Corp. 2016. HTC VIVE. (2016). `http://vive.com/en/`.

[8] James N Druckman and Arthur Lupia. 2000. Preference formation. *Annual Review of Political Science* 3, 1 (2000), 1–24.

[9] Thomas Erickson and Wendy A Kellogg. 2000. Social translucence: an approach to designing systems that support social processes. *ACM transactions on computer-human interaction (TOCHI)* 7, 1 (2000), 59–83.

[10] Jeffrey A Greenberg, John F Burke, Rafi Haque, Michael J Kahana, and Kareem A Zaghloul. 2015. Decreases in theta and increases in high frequency activity underlie associative memory encoding. *Neuroimage* 114 (2015), 257–263.

[11] F Maxwell Harper and Joseph A Konstan. 2016. The movielens datasets: History and context. *Acm transactions on interactive intelligent systems (tiis)* 5, 4 (2016), 19.

[12] Looxid Labs US Inc. 2019. Looxid Pro. (2019). `http://pro.looxidlabs.com/`.

[13] Eric P Kroes and Robert J Sheldon. 1988. Stated preference methods: an introduction. *Journal of transport economics and policy* (1988), 11–25.

[14] Jakob Nielsen and Jonathan Levy. 1994. Measuring usability: preference vs. performance. *Commun. ACM* 37, 4 (1994), 66–76.

[15] Paul Rozin and Edward B Royzman. 2001. Negativity bias, negativity dominance, and contagion. *Personality and social psychology review* 5, 4 (2001), 296–320.

[16] Avgusta Y Shestyuk, Karthik Kasinathan, Viswajith Karapoondinott, Robert T Knight, and Ram Gurumoorthy. 2019. Individual EEG measures of attention, memory, and motivation predict population level TV viewership and Twitter engagement. *PloS one* 14, 3 (2019), e0214507.

[17] Paul Slovic. 1995. The construction of preference. *American psychologist* 50, 5 (1995), 364.

[18] Hao-Chuan Wang, Tau-Heng Yeo, Syavash Nobarany, and Gary Hsieh. 2015. Problem with Cross-Cultural Comparison of User-Generated Ratings on Mechanical Turk. In *Proceedings of the Third International Symposium of Chinese CHI*. ACM, 9–12.

[19] Yu-Kai Wang, Tzyy-Ping Jung, and Chin-Teng Lin. 2018. Theta and alpha oscillations in attentional interaction during distracted driving. *Frontiers in behavioral neuroscience* 12 (2018), 3.

[20] Caleb Warren, A Peter McGraw, and Leaf Van Boven. 2011. Values and preferences: defining preference construction. *Wiley Interdisciplinary Reviews: Cognitive Science* 2, 2 (2011), 193–205.

[21] Thorsten O Zander and Christian Kothe. 2011. Towards passive brain–computer interfaces: applying brain–computer interface technology to human–machine systems in general. *Journal of neural engineering* 8, 2 (2011), 025005.