APPLICATION OF NEURAL TECHNOLOGY TO NEURO-MANAGEMENT AND NEURO-MARKETING

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APPLICATION OF NEURAL TECHNOLOGY TO NEURO-MANAGEMENT AND NEURO-MARKETING

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Editorial: Application of Neural Technology to Neuro-Management and Neuro-Marketing

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Keywords: neuromarketing, neuromanagement, brand preference, consumer, ERPs

Editorial on the Research Topic

Application of Neural Technology to Neuro-Management and Neuro-Marketing

Marketing studies the management of exchange relationships, while brand management deals with the relationship between a company's product and emotional perception of customer in terms of expectations and satisfaction. Here we are set to assess work on neuro-management and neuro-marketing by investigating the neural features of customer/consumer behavior.

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BRAND MANAGEMENT

Several reports describe the brand management in terms of brand preferences, brand extension, personalized preference, perception and framing of price, and hazard perception (in term of financial decision making).

Brand Preference

The preference for a certain brand in the context of brand competition is a sign of customer loyalty. Yu et al. examined brand preference rating by recording ERPs to analyze brain activity during brand information processing when subjects/customers experienced victory or defeat. Behavioral results showed that subjects exhibited a stronger preference for "unfamiliar" brands in victory trials, even if the brand was totally unrelated to the competition. The existence of "incidental emotions" induced by victory or defeat were reflected in the elicited ERPs, more negatively in victory than in defeat trials. These findings indicate that victory/defeat contexts can evoke "incidental emotions" that induce preference for unfamiliar brands.

The customers' preference is biased to their local brands over the foreign ones. This tendency is known was coined as consumer ethnocentrism. Ma, Abdeljelil et al. employed the event-related potential (ERP) approach to identify consumer ethnocentrism on brand preference in terms of neural activity and behavioral responses on two groups of subjects. One group consisted of Chinese subjects and the other group was formed by Black Africans. The results pointed out that the race significantly impacted the Chinese subjects' brand preference. There was also evidence that familiarity with foreign cultures reduces consumer's ethnocentrism. African subjects being familiar with Chinese people had similar brand preferences.

Brand Extension

Brand extension is a marketing approach in which a new product such as goods or service is launched under an established brand name. It distinguishes two strategies: brand name extension (BN) and brand logo extension (BL). Shang et al. assessed which of the two strategies (BN or BL) better increased the success of dissimilar brand extension. Behavioral outcomes demonstrated that BL was accepted better than BN in the dissimilar brand extension. At the neurophysiological level, the brand extension process was characterized by a less negative N2 and a larger P300 in the BL compared to BN. Yang and Kim compared ERPs between population-fit groups and found significant differences in the fronto-central N2 and fronto-parietal P300 amplitudes. Their findings indicate that left fronto-parietal P300 may yield the evidence for brand extension to service, which may require retrieval of semantic memory and categorization of similarity. Similarly, Yang T. et al. reported ERP analysis that identified three components during the evaluation of brand extension: N2, P300, and N400. Shang et al. indicated that N2 reflected a conflict between the brand-product combination and the long-term memory and that P300 could be regarded as the reflection of the categorization process in the working memory.

Personalized Preference

Neuroscientific methods are preferred to gain insight into the neural basis of consumers' evaluation of experience good designs. Ma Y. et al. used "personalized" T-shirt designs as stimuli, while recording ERPs in a modified go/no-go task to investigate consumers' neural responses to experience good designs. Results show that both ERP components, P200 and the late positive potential (LPP), were high in response to the best-preferred product designs vs. the least-preferred designs, when subjects saw the product designs without making a decision. These findings shed light on the reasons why consumers like customized products.

Price: Perception and Framing

Two studies are reporting on price perception and the temptation of zero price, while providing evidence on price framing in purchase decision making Emotion was demonstrated to be ubiquitous in marketing and influenced purchase processing as well. The study by Ma, Zhang et al. examined whether emotion arousal would influence consumers' price perceptions and their willingness to purchase. Both behavioral and ERP results indicated that subjects' price perception was deeply impacted by emotions induced from continuous win/lose experiences.

Ma H. et al. employed the ERPs approach to investigate the role of "price framing" in information processing and purchase decision making in a bundling context. Results provide both behavioral and neural evidence for how different price framing information is processed and ultimately gives rise to price framing effect in purchase decision making.

Hazard Perception and Financial Decision Making

A couple of papers report on the "hazard perception" for the warning signs and on the sequential organization of information for financial decision-making. Ma, Bai et al. used ERP technology and the "Oddball paradigm" to evaluate the impact of the shapes on the perception of warning signs, and to discover the neural substrate of the "hazard perception" of the shapes by electrophysiological characterization. Results indicated that the shape of "upright triangle" provides larger arousal intensity and more "negative valence" than the shape of "circle." Stronger negative information comes from the "upright triangle" shapes than from the "circle." This finding may be useful for designing the shapes surrounding warning signs.

Yang W. et al. have evaluated the case when the evidence and information are in a sequence and have found that order effect and biases have an impact in various areas. The behavioral outcomes, which are an investment decision, were consistent with the idea that individuals will invest more/retire less when receiving the information in a negative-positive order. The results suggest that in the scheme that involve large-scale information, the organization of information (integration vs. segregation) influences the emotion and approach-withdraw trend. Deppe et al. (2005) further add that nonlinear responses within the medial prefrontal cortex reveal when specific implicit information is influencing the process of economic decision making.

USE OF NEURAL TECHNOLOGY IN MARKETING RESEARCH

The reports below describe the application of the neural technology in marketing research in combination with: fNRI, lie detection, advertisement research, fake rating behavior in e-commerce and stereotypes activated by media.

fNIRS in Marketing Research

Krampe et al. investigated—likely for the first time ever- the validity of the mobile functional near-infrared spectroscopy (fNIRS) in (neuro-) marketing research. Successfully, the authors managed to replicate the second sub-effect (reduced activity in dlPFC) but as they hypothesized, they failed to replicate the first sub-effect (reduced activity in vmPFC) of the "*first-choice-brand*" effect (Deppe et al., 2005) using mobile fNIRS. Therefore, it might be concluded that if neuromarketing researchers are interested in measuring activity in dlPFC, mobile fNIRS offers them more affordable and ecologically valid tool than fMRI, at least while measuring the "first-choice-brand" effect.

Lie Detection

Growing interest and importance of the fNIRS is additionally strengthened by Li F. et al. (this Research Topic) study of a topic inextricably linked to (neuro-) management—detection of infrequent and frequent liars. The authors specifically found that "while performing deception detection tasks, infrequent liars showed significantly greater neural activation in the left MFG than the baseline, but frequent liars and innocents did not exhibit this pattern of neural activation in any area of inhibition-related brain regions" (p. 1). Li D. et al.'s findings and application of fNIRS—during for example prisoner's dilemma—might shed further light on that cornerstone of the game theory and modern management decision-making and further unite neuroscience and management fields.

Advertisement Research

Several papers discuss topics of modern advertisement research involving novel technology based on support vector machine for impact assessment, willingness to pay reflected in brain activity, fake rating in e-commerce, and racial stereotypes activated by media.

The current Research Topic reports two studies which focus on application of electroencephalography (EEG) to the advertisement research. Ramsøy et al. established a relation between widely studied willingness to pay (WTP) measure and EEG responses: the prefrontal gamma asymmetry and a trend in the beta frequency band. Then, importantly, Wei et al. developed—based on data from 220 different video advertisements—a novel artificial intelligence algorithm (Support Vector Machine; SVM) to predict WTP (just like Ramsøy et al.) by using neural responses but from a consumer-grade (and hence low-cost) EEG headset; with an accuracy of around 75%. Taken together, these studies significantly advance the study of neuromarketing.

Fake Rating Behavior in E-Commerce

In a study on e-commerce, Wang et al. explored whether a certain strategy was more likely to give rise to false rating behaviors, as assessed by ERPs. A two-stimulus paradigm was used to show that five-star ratings strategy led to a higher rate than the other. The findings provide evidence supporting the policy of forbidding the use of the "five stars rating" strategy in e-commerce.

Racial Stereotypes Activated by Media

Stereotypes from the major nationality toward minorities constitute a widely concerning problem in many countries. The study by Jin et al. focused on the neural basis of the modulation of negative media information on Han Chinese stereotypes toward Uyghurs by using ERPs measures. The results suggested that the negative media information might influence their judgments toward other groups reflected in the deflection of N400 amplitude. Therefore, in order to mitigate or even eliminate stereotypes about national minorities, the effort of the media is important.

NEURAL CORRELATES OF NEUROMARKETING

Several reports describe the neural correlates of: monetary incentive delay, self-motivation, preference, consumer buying motivations, reputation learning, the relationship between challenge and motivation, and the neural features of safety inspections.

Monetary Incentive Delay

Krugliakova et al. investigated whether an auditory version of the monetary incentive delay task could modulate brain plasticity when processing incentive cues that code for expected monetary outcomes. Interestingly, they found that after only 2 days of training, auditory stimuli predicting reward evoked a larger involuntary neural response than that in the baseline condition. Their result suggests that the sensory processing of incentive cues is dynamically adjusted by the expectation of a reward.

Self-Motivation

Within the framework of the self-determination theory, Fang et al. examined restorative processes occurring when competence, one of the basic psychological predictor of one's wellbeing, is frustrated. To this effect, they manipulated competence frustration in a between-group experimental design, and observed an enlarged frustration-related neural response in the experimental group, as compared to controls. Such results document the neural correlates of complex restoration process and can help refine future managerial practice.

Neural Correlates of Preference

Akiba et al. explored the physiological markers of likeability judgements, a crucial element in value-based evaluation, the building brick of the reward system. To this effect, they developed a method capable of tracking bodily reactions to dynamic video stimuli and were able to identify robust time-dependent markers of pleasure/displeasure judgements.

Neural Correlates of Consumer Buying Motivations

In their study, Goodman et al. used functional magnetic resonance imaging (fMRI) to assess and contrast the neural correlates of various types of buyer's motivations for ordinary consumer goods. The results segregated different patterns of activations with symbolic buying motivation associated more with medial frontal gyrus (MFG) BOLD signal, experiential motivation associated more with posterior cingulate cortex (PCC) activation, and functional motivation associated more with activity in the dorsolateral prefrontal cortex (DLPFC). These findings elucidate some of the neural underpinnings of reduced self-control.

Reputation Learning

In an event-related potential (ERP) study, Li D. et al. explored the reputation learning process in a repeated trust game where subjects made multiple round decisions of investment to partners. They found that subjects gradually learned to discriminate trustworthy partners from untrustworthy ones based on how often their partners reciprocated the investment. In the late stages of the game, this discrimination was matched in the electrophysiology, where the faces of untrustworthy partners induced larger feedback negativity (FN) than those of trustworthy partners. This result highlights the fact that the FN reflects the reputation appraisal and is useful to tracks reputation learning in social interactions.

Relationship Between Challenge and Motivation

The balance between task demand and one's competence is critical for the maintenance of motivation. Ma, Pei et al. employed the inverted U-shaped curve to depict the relationship between a player's perceived challenge and his motivation. The electrophysiological results confirmed the inverted U-shaped curvilinear relationship between perceived challenge and one's intrinsic motivation.

Neural Features of Safety Inspections

The study by Ma, Shi et al. used ERPs to investigate the neurocognitive signatures of "severe-and-deterrent phrases" and "mild-and-polite phrases" used by OHS inspectors. The ERP results demonstrated that first type of phrases convey a higher level of severity and motivation compared with the second type of phrases, that exhibited a significantly incremented P300 amplitude. The study by Ma, Shi et al. provides an objective method to quantify the efficiency of "enforcement phrases," which may help to enhance quality of OHS inspections.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

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Neural Features of Processing the Enforcement Phrases Used during Occupational Health and Safety Inspections: An ERP Study

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The appropriate enforcement phrases used during occupational health and safety (OHS) inspection activities is a crucial factor to guarantee the compliance with OHS regulations in enterprises. However, few researchers have empirically investigated the issue of how enforcement phrases are processed. The present study explored the neural features of processing two types of enforcement phrases (severe-and-deterrent vs. mild-and-polite phrases) used during OHS inspections by applying event-related potentials (ERP) method. Electroencephalogram data were recorded while the participants distinguished between severe-and-deterrent phrases and mild-and-polite phrases depicted in written Chinese words. The ERP results showed that severe-and-deterrent phrases elicited significantly augmented P300 amplitude with a central-parietal scalp distribution compared with mild-and-polite phrases, indicating the allocation of more attention resources to and elaborate processing of the severe-and-deterrent phrases. It reveals that humans may consider the severe-and-deterrent phrases as more motivationally significant and elaborately process the severity and deterrence information contained in the enforcement phrases for the adaptive protection. The current study provides an objective and supplementary way to measure the efficiency of different enforcement phrases at neural level, which may help generate appropriate enforcement phrases and improve the performance of OHS inspections.

Keywords: occupational health and safety, P300, attention, event-related potentials, neuromanagement

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INTRODUCTION

Nowadays, the occupational health and safety (OHS) issue has attracted more and more attention from the enterprises, governments, as well as researchers because of its close relationship to the vital interests of the workers and great importance to enterprises' operation and performance (Fernández-Muñiz et al., 2009). Among multiple factors influencing the implementation of OHS management system in the enterprises, the OHS inspections from the enforcement agencies play an important role in ensuring the enterprises' compliance with OHS legislation and guaranteeing the workers' OHS in good status (Niskanen et al., 2014; Hale et al., 2015; Kvorning et al., 2015). The enforcement phrases used by inspectors have a direct impact on the workers and managers' responses to enforcement actions, which is a key factor to make the regulations of OHS practicable and encourage the compliance (Fernández-Muñiz et al., 2009; Kvorning et al., 2015). Generally, the enforcement phrases can be broadly categorized into severe-and-deterrent phrases and mild-and-polite phrases according to two enforcement strategies (deterrence and punishment strategy or advice and persuasion strategy; Niskanen et al., 2014; Hale et al., 2015). Until now, few researchers have studied the cognitive processing of the enforcement phrases and the differences in processing between the two types of phrases. It is still not clear whether the severity and deterrence information are conveyed by the enforcement phrases and humans can identify them. The aim of this study is to address these issues at the neural level.

Emotional stimuli always capture more attention and are elaborately processed since they are important for human's survival, preservation and reproduction (Lang et al., 1997; Schupp et al., 2007). Words/phrases, pictures and facial expressions are commonly used as the stimuli to study the emotion processing (Schupp et al., 2004; Olofsson et al., 2008; Citron, 2012). As a powerful communication way, words or phrases are efficient to convey emotion contents and cognitive contents, which are valuable for human's life, for example, alert humans to hazard or risk in a hazardous environment (Qin and Han, 2009; Ma et al., 2010; Citron, 2012; Shang et al., 2015). Some words directly express the emotional state (e.g., happy, sad) while others denote the emotional connotation (e.g., reward, danger; Citron, 2012). Several studies find words/phrases with emotional connotation do not merely modulate the allocation of attention, they can also convey some valuable information that lead to further cognitive processing (Qin and Han, 2009; Ma et al., 2010; Shang et al., 2015). For instance, the hazard information contained in the warning signal words (e.g., danger, urgent; Ma et al., 2010) and the environment risk information embedded in the words/phrases depicting environmental events (e.g., earthquake, air pollution; Qin and Han, 2009) can be identified and further evaluated by humans. In order to explore the cognitive mechanisms underlying the emotional stimuli processing, many studies apply the event-related potentials (ERPs), which provides high temporal resolution and allows a finer examination of the amount of time and resources allocated to stimuli evaluation (Hillyard and Kutas, 1983). One of the ERP component associated with the emotional stimuli processing is the P300, which is a positive ERP component with a peak latency at around 300 ms after the onset of stimuli (Polich, 2007; Olofsson et al., 2008; Citron, 2012). Multiple studies indicate that P300 demonstrates the neural activity associated with cognitive operations and larger amplitude reflects the more attention resources engaged for stimuli processing (Kok, 2001; Polich, 2007; Schupp et al., 2007; Shang et al., 2015). Previous ERP studies about the emotion processing reveal that high-arousal stimuli often elicit enlarged P300 than low-arousal stimuli, indicating more attention resources are allocated to process the high-arousal stimuli (Delplanque et al., 2006; Olofsson et al., 2008; Citron, 2012; Recio et al., 2014; Delaney-Busch et al., 2016). Ma et al. (2010, 2014) categorized the warning signal words and pictures into high-hazard and low-hazard groups according to the arousal strength rating and found high-hazard group evoked larger P300 amplitude in the task of judging the stimuli as high-hazard or low-hazard. Moreover, in an implicit task without emotional categorization, the threatening faces (Schupp et al., 2004) with high-arousal level also elicited augmented P300 compared to the neutral and friendly face expressions that were less arousing. Such effect is also observed in other emotion processing studies using various implicit tasks (e.g., lexical decision task; Schupp et al., 2007; Scott et al., 2009; Citron, 2012; Delaney-Busch et al., 2016). These findings suggest that arousal effect on the attention allocation reflected by enlarged P300 exists in both passive viewing and active response tasks (Olofsson et al., 2008).

The most methodologies used in the OHS empirical studies are the survey and interview, which are based on the self-report data (Fan et al., 2014). To our knowledge, there are few studies using the electrophysiology method, such as ERP, to explore cognitive processes underlying the human's processing of enforcement phrases in OHS area. Based upon the previous studies that suggest words and phrases can convey cognitive contents (e.g., hazard and risk information; Qin and Han, 2009; Ma et al., 2010), we assumed that enforcement phrases applied by inspectors during the OHS inspections may convey severity and deterrence information of different arousal levels and the severe-and-deterrent enforcement phrases were high-arousal stimuli, which contain more obvious severity and deterrence information than mild-and-polite phrases. Thus, more attention resources would tend to be devoted to elaborately process the severe-and-deterrent enforcement phrases, evoking larger P300 than the mild-and-polite phrases. In order to examine this assumption, we conducted an ERP experiment with the task of judging whether the enforcement phrase was severe-and-deterrent or not.

MATERIALS AND METHODS

Participants

Sixteen right-handed students (9 females; mean age: 21.50 years, $SD = 2.03$) in Zhejiang University participated in this experiment. All participants had normal or corrected-to-normal vision. None of them reported any history of psychiatric or neurological disorders. They were fully informed of the experiment procedure and provided written consent. They obtained adequate remuneration after the experiment. The study was approved by the Neuromanagement laboratory's ethics committee in Zhejiang University.

Experimental Stimuli

First, we selected 60 enforcement phrases used in OHS inspections from the regulations and documents (e.g., Law enforcement behavior standards of administrative personnel, Civilization Law enforcement terms norms of urban management, and Note of workplace occupational health supervision and inspection provisions) issued by the central government or some local governments. Second, we recruited sixty participants who would not participate in the ERP experiment to assess the perceived arousal strength of severity and deterrence of each enforcement phrase on a five-point Likert scale (1 = the most mild and polite, and 5 = the most severe and deterrent). Last, we chose 30 enforcement phrases out of the initial 60 and categorized them into two groups according to their rating scores. One group comprised 15 severe-and-deterrent phrases (e.g., "you are imposed with a disciplinary warning as a sanction," "eliminate hazards immediately," "we will execute compulsory inspection," etc.) with an average of 3.653 (SD = 0.611), while the other group comprised 15 mild-and-polite phrases ("Hello! Please show your ID," "please send someone to help with inspection," "please confirm and sign your name," and so forth) with an average of 2.660 (SD = 0.518). The alpha reliability coefficients were 0.891 for the severe-and-deterrent group and 0.819 for the mild-and-polite group. The difference in rating scores between the two groups was significant ($t = 12.08$, $p < 0.001$). The number of Chinese characters in each phrase was five to seven and was not significantly different between the two groups [mean number of characters: 6.67 (severe-and-deterrent) vs. 6.53 (mild-and-polite); $t = 0.642$, $p = 0.526$].

Procedure

During the experiment, participants sat comfortably in an electrically shielded and acoustically isolated room, while their electroencephalogram (EEG) was simultaneously recorded. The enforcement phrases were displayed on a 17″ CRT screen 1 m away from them. The stimuli were presented by the E-Prime 2.0 Software Package (Psychology Software Tools, Pittsburgh, USA) and they subtended ~6.5° × 6.2° of visual angle. Each participant completed 90 trials in the experiment. In each trial, a black fixation cross was presented for 500 ms at the center of the screen followed by a random interval between 500 and 700 ms. Then, an enforcement phrase was presented for 2000 ms. Once the phrases appeared, participants were required to press the key button 1 or 3 to indicate the group (the severe-and-deterrent or the mild-and-polite) of the phrases as soon as possible. The key button corresponding to each group was counterbalanced across participants. Each phrase was in Chinese Song typeface with black color against a gray background and was presented for three times. Finally, a gray screen appeared for 500 ms before the next trial. The sequence of the 90 trials was random. Before the main ERP experiment, the participants practiced for ten trials. The whole experiment would not last for more than 6 min.

EEG Recording

EEG was continuously recorded with a Neuroscan Synamp2 Amplifier (Scan 4.3.1, Neurosoft Labs, Inc. Virginia, USA) with 64 Ag/AgCl electrodes positioned according to the International 10–20 System (band pass: 0.05–100 Hz; sampling rate: 500 Hz). All electrodes were first referenced to the left mastoid and later digitally re-referenced to the linked mastoids. Vertical and horizontal electrooculograms (EOGs) were monitored with two pairs of electrodes. One pair was placed above and beneath the left eye in parallel with the pupil, and the other at the outer canthus of each eye. All electrode impedance was maintained below 5 kΩ.

Data Analysis

Offline analysis of the recorded EEG data included the following procedures by using Scan 4.5 software (Compumedics NeuroScan Inc., Herndon, Virginia, USA): vertical ocular artifact correction using the regression approach described by Semlitsch et al. (1986), digitally low-pass (30 Hz, 24 dB/Octave) filtering, segmenting EEG data into epochs of 1000 ms (from 200 ms before to 800 ms after the phrases stimuli onset), baseline correction (data in the pre-stimuli period served as baseline). Epochs with peak-to-peak deflection exceeding ±80 μV were excluded from later ERP averaging. Finally, the data were averaged separately for severe-and-deterrent phrases and mild-and-polite phrases.

Similar to previous related studies (Kok, 2001; Olofsson et al., 2008), we observed the P300 component mainly distributed over the central-parietal regions (see the topographic maps in **Figure 1**). On the basis of visual inspection, P300 was measured as the mean amplitude of the time window from 320 to 400 ms, and we selected 6 electrodes of CP3, CPz, CP4, P3, Pz, and P4 for statistical analysis. Within-participant repeated-measures analyses of variance (ANOVAs) were performed to examine the effects of phrase type (severe-and-deterrent vs. mild-and-polite) and electrode on the P300 component. The Greenhouse-Geisser correction was applied for the violation of the sphericity assumption in ANOVA [uncorrected degrees of freedom are reported with corrected p-values and epsilon values (ε)], and multiple comparisons were corrected with the Bonferroni method when appropriate.

RESULTS

Behavioral Results

The paired t-test showed that the reaction time was not significant between severe-and-deterrent enforcement phrases and the mild-and-polite enforcement phrase ($t = -1.929$, $p = 0.073$), although the reaction time to distinguish severe-and-deterrent phrases was longer (Mean = 960.315 ms, SD = 113.921 for severe-and-deterrent; Mean = 903.058 ms, SD = 166.158 for mild-and-polite).

ERP Results

The grand average waveforms of P300 are shown in **Figure 1**. The dashed line represents the severe-and-deterrent enforcement phrases and the solid line represents the mild-and-polite enforcement phrases. The 2 (Phrase type: severe-and-deterrent vs. mild-and-polite) × 6 (Electrodes: CP3, CPz, CP4, P3, Pz, P4) repeated-measures ANOVAs showed that the main effect of phrase type was significant [$F_{(1, 15)} = 8.088$, $p = 0.012$]. The enforcement phrases in the severe-and-deterrent group elicited larger P300 than the phrases in the mild-and-polite group did (mean = 7.6270, SD = 4.4243 for severe-and-deterrent phrase; mean = 6.6941, SD = 3.8164 for mild-and-polite phrase). The electrode effect was not significant ($p > 0.1$).

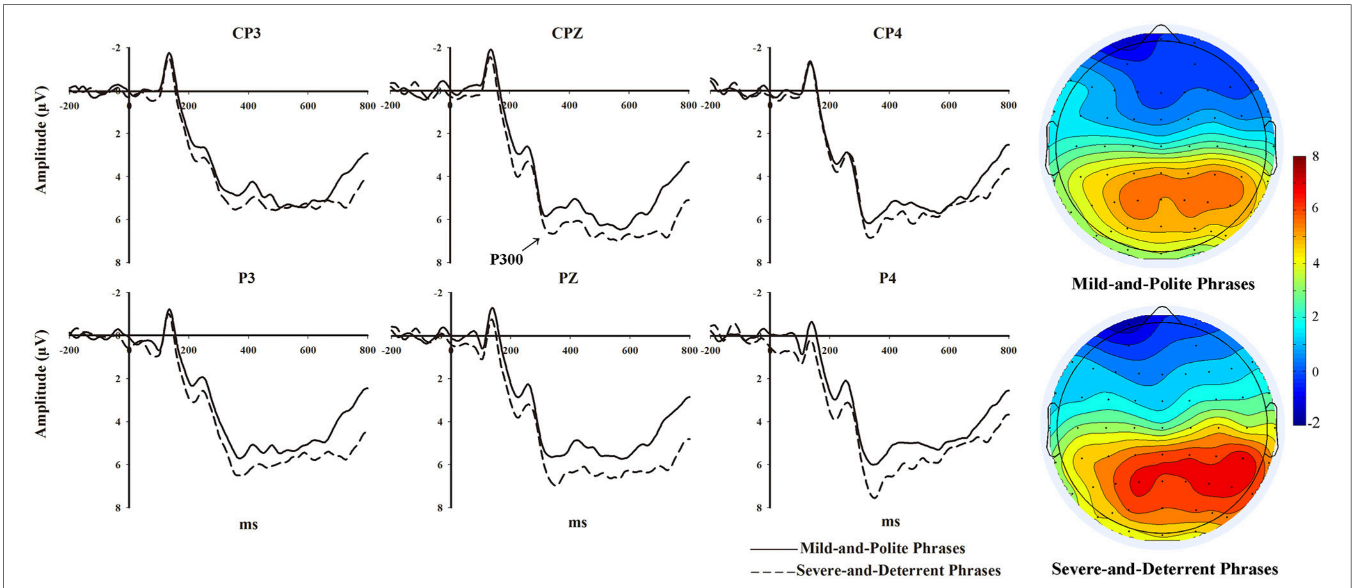

FIGURE 1 | The grand average waveforms of P300 and topographic maps in 320–400 ms time window.

DISCUSSION

The present study investigated the neural activities underlying the processing of two types of enforcement phrases (severe-and-deterrent vs. mild-and-polite) used during the OHS inspections by means of an explicit evaluation task (judging the phrase as severe-and-deterrent vs. mild-and-polite). Behavioral results showed that the reaction times of distinguishing these two types of enforcement phrases were not significantly different. As for ERP results, both the severe-and-deterrent enforcement phrases and the mild-and-polite phrases evoked P300 waveforms with a central-parietal scalp distribution. The severe-and-deterrent phrases elicited a significantly augmented P300 than the mild-and-polite phrases did. It indicated that the participants devoted more attention resources to elaborately process the severe-and-deterrent phrases.

P300 component is regarded as a neural index of intensity of stimuli evaluation and measurement of attention resource allocated to the task or stimuli (Kok, 2001; Polich, 2007; Schupp et al., 2007). A classic finding is that motivationally significant stimuli (e.g., emotional value and task-relevance) receive preferential attention to be processed and thus elicit enlarged P300 (Kok, 2001; Schupp et al., 2007). In most ERP studies regarding the emotion processing, larger P300 amplitude is evoked by high-arousal stimuli than low-arousal ones (Delplanque et al., 2006; Olofsson et al., 2008; Citron, 2012; Recio et al., 2014; Delaney-Busch et al., 2016). This preferential attention and elaborate processing may result from the high intrinsic motivational properties of the high-arousal stimuli (e.g., high hazard, risk, and threat), which enhance the encoding processing of the stimuli (Lang et al., 1993; Azizian and Polich, 2007; Olofsson et al., 2008). High-arousal stimuli are seen as motivationally significant insofar as they are relevant to human's survival, preservation, and reproduction (Lang et al., 1997; Schupp et al., 2007; Kousta et al., 2009). For example, risky environment events such as floods and earthquakes would lead to catastrophic consequences, which are relevant to the survival of a lot of people. Hence, the words or phrases depicting such risky events induce more brain activation (a larger central-parietal late positive potential) for processing than that depicting safe events (Qin and Han, 2009). Other high-arousal stimuli including warning words (Ma et al., 2010; Shang et al., 2015), hazardous pictures (Ma et al., 2014), and threatening faces (Schupp et al., 2004) are relevant to human's safety and thus elicit larger P300. Qin and Han (2009) suggested that human can extrapolate the severe and dreadful consequence associated with the risky environmental event depicted by words/phrases and retrieve related emotional experience. Ma et al. (2010, 2014) found humans could evaluate the hazard level of hazardous stimuli and had a stronger emotion reaction when confronted with high-hazard stimuli. In present study, the severe-and-deterrent phrases used to enforce the inspections of OHS have higher arousal level of severity and deterrence than mild-and-polite phrases. These obvious severity and deterrence information conveyed by the severe-and-deterrent enforcement phrases may lead to the dread about severe and punitive consequences inferred from the phrases if violating the regulations and are important for the rapid modifications of behavior for preservation or protection (Lang et al., 1997; Kousta et al., 2009). This motivationally relevant information can be identified by the humans and occupy more attention resources to be processed elaborately. Therefore, severe-and-deterrent enforcement phrases are regarded as motivationally significant stimuli and are more likely to provoke the humans' motivation system in the brain compared with mild-and-polite phrases, represented by enlarged P300. In accordance with previous ERP studies related to the emotional stimuli processing (Keil et al., 2002; Schupp et al., 2007; Olofsson et al., 2008), we also found a central-parietal scalp distributed P300 for the processing of both severe-and-deterrent and mild-and-polite phrases at later stage.

Before the current study, there were only survey and interview studies with respect to OHS and few explored the cognitive mechanism underlying the processing of different enforcement phrases used during OHS inspections. This study, for the first time, explores the cognitive processes involved in enforcement phrases processing by using ERP measure. We find the P300 is sensitive to the severity and deterrence level and suggest this neural indicator may serve as an objective and supplementary way to measure the efficiency of enforcement phrases and guide the generation of appropriate enforcement phrases, which should reach enough severity and deterrence level.

In sum, the current study indicates the different neurocognitive processes involved in the processing of severe-and-deterrent phrases and mild-and-polite phrases used by inspectors of OHS. Severe-and-deterrent phrases convey higher level of severity and deterrence and are regarded as more motivationally significant. Therefore, such phrases attract more attention and have the advantage to be processed elaborately compared with the mild-and-polite phrases, reflected by augmented P300 amplitude. It reveals that humans indeed process the severity and deterrence information contained in the enforcement phrases. Besides, our study first shows the possibility of application of neuroscience tools (electrophysiological measurement) in the safety science to measure the efficiency of enforcement phrases and improve the quality of inspections and OHS performance.

AUTHOR CONTRIBUTIONS

QM, LS, and QW conceived and designed the experiments. QL, LH, and ZY performed the experiment. LH and QL analyzed the data. QM, LS, and LH wrote and refined the article.

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CORRECTION
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Corrigendum: Neural Features of Processing the Enforcement Phrases Used during Occupational Health and Safety Inspections: An ERP Study

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Logo Effects on Brand Extension Evaluations from the Electrophysiological Perspective

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Brand extension typically has two strategies: brand name extension (BN) and brand logo extension (BL). The current study explored which strategy (BN or BL) better enhanced the success of dissimilar brand extension and product promotion in enterprises. Event-related potentials (ERPs) were used to investigate electrophysiological processes when subjects evaluated their acceptance of the brand extension using a combined picture of S1 and S2. S1 was a famous brand presented by two identity signs (brand name and brand logo). S2 was a picture of an extension product that belonged to a dissimilar product category than S1. The behavior data showed that BL was more acceptable than BN in the dissimilar brand extension. The neurophysiology process was reflected by a less negative N2 component and a larger P300 component in the BL than in the BN. We suggested that N2 reflected a whole conflict between the brand-product combination and the long-term memory and that P300 could be regarded as the reflection of the categorization process in the working memory.

Keywords: brand name, brand logo, dissimilar brand extension, N2, P300, neuromanagement

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INTRODUCTION

Brand extension is the use of an established brand to launch a new product (Aaker, 1990; Völckner and Sattler, 2007), which serves as a critical and widespread product promotion strategy in the enterprise (Hem et al., 2003; Völckner and Sattler, 2007). A great deal of existing evidence supported the notion that brand extension obtained a higher acceptance rate when the categories of the parent brands and extension products were similar (similar brand extension) than when they were dissimilar (dissimilar brand extension; e.g., Ma et al., 2008, 2010; Jin et al., 2015). However, the dissimilar brand extension strategy also plays an important role in entering new markets for enterprises. Thus, enhancing the success of dissimilar brand extension remains a critical issue worth studying.

Aaker and Keller (1990) constructed a theoretical framework (the consumer evaluation model of brand extensions) to research the factors that influenced brand extension success. This model showed that the success of brand extension depended on the consumer's perception of how well the extension products matched the parent brand (Aaker and Keller, 1990). This finding meant that a higher perceived fit was related to a more positive evaluation of the brand extension (MacInnis and Nakamoto, 1990; Boush and Loken, 1991; Bhat and Reddy, 2001). Based on this model, the overwhelming majority of brand extension studies have focused on the perceived fit between the names of the parent brands and the extension products (e.g., Ma et al., 2008, 2014b; Wang et al., 2012; Jin et al., 2015). For example, a brand extension study by Ma et al. (2008) indicated that a higher perceived similarity and coherence between the brand name and the product name resulted in higher brand extension success. Ma et al. (2014b) suggested that a two-stage categorization process (early low-level and similarity-based processing and late analytic and category-based processing) was involved in the evaluation process of perceived fit between the names of the parent brands and the extension products (Ma et al., 2014b). However, a parent brand can primarily be identified by not only its brand name but also its brand logo (Fombrun and Van Riel, 1997; Klink, 2003; Guzmán et al., 2012). Although brand extension appears to have two important extension strategies (brand name extension and brand logo extension), few studies concerning the strategy of brand logo extension have been performed to date. Thus, it is necessary to conduct a study to examine which brand extension strategy (brand name extension or brand logo extension) is better for improving a consumer's perceived fit and enhancing the success of dissimilar brand extension.

Generally, the brand name is more simple and familiar information to consumers and is better stored in their long-term memory than the brand logo (Baxter et al., 2015). However, some studies demonstrated that the stereotypes of customers toward familiar brand information in their long-term memory could lead them to a better fit with the original product category but a worse fit with other product categories (Jin et al., 2015). In contrast, for unfamiliar brand information not stored in a consumer's long-term memory, the consumer's perceived fit between the brand information and the original product category was the same as that between the brand information and a dissimilar product category (Jin et al., 2015). Therefore, we hypothesized that the brand logo was more suitable than the brand name when a brand was extended to a dissimilar category product. Thus, the brand logo extension strategy was better compared to the brand name extension strategy in improving a consumer's perceived fit and enhancing the success of dissimilar brand extension.

To investigate how different evaluations on the brand logo extension and the brand name extension were implemented in the brain, we measured event-related potentials (ERPs) using physical picture stimuli (i.e., brand-product picture combination). ERPs are important measures of perceptual and cognitive processing of stimuli and have a high temporal resolution (Luck et al., 2000). This approach could help investigate the whole time course of the consumer's brand extension evaluation process.

N2 is an event-related potential with a negative wave peaking between 200 and 400 ms post-stimulus (Folstein and Van Petten, 2008; Dickter and Bartholow, 2010). A series of ERPs studies suggested that N2 reflected conflict and mismatch from a visual template (Van Veen and Carter, 2002; Folstein and Van Petten, 2008). For example, the N2 component has been found to have a larger amplitude when the second stimulus (S2) in a pair does not match the physical attributes of the first stimulus (S1), such as color (Semlitsch et al., 1986; Cui et al., 2000; Wang et al., 2004; Han et al., 2015), shape (Cui et al., 2000; Zhang et al., 2001; Wang et al., 2004; Han et al., 2015), orientation (Wang et al., 1998), position (Yang and Wang, 2002; Mao and Wang, 2008), or digit value (Kong et al., 2000). In these studies, the information from the S1 was first encoded into the working memory system. When the information from S2 was transmitted into the brain, the memory information from S1 was retrieved and compared with the information from S2. The difference between S2 and S1 led to memory conflict and elicited the N2 component (Han et al., 2015). In addition to the conflict between these physical attributes, perception conflict could also evoke the N2 component. For example, Ma et al. (2007, 2010) observed a greater N2 amplitude when participants perceived stronger conflict between the brand (S1) and the extension product (S2) in brand extension evaluations. The authors suggested that this perceived conflict effect resulted from the comparison of the product (S2) attribute to the brand's (S1) product attribute in the brand memory (Ma et al., 2007). Thus, it is reasonable to hypothesize that the N2 component may index as an automatic detection of memory conflict for the stimulus materials. In the current study, we hypothesized that a N2 component would be elicited by the memory conflict when the brand was extended to a dissimilar category product. Furthermore, if the brand logo extension led to a higher perceived fit compared to the brand name extension, we hypothesized that this higher fit could be reflected by a smaller memory conflict and N2 amplitude in the brand logo extension than in the brand name extension.

In addition to N2, P300 represents different aspects of the stimulus evaluation (Yeung and Sanfey, 2004; Xu et al., 2011). P300 is a positive ERPs component with a peak latency between 300 and 1,000 ms after the stimulus onset that reflects the activity of event categorization in the working memory (Kok, 2001; Zhang et al., 2003; Azizian et al., 2006; Ma et al., 2008). In a probe-matching experiment by Zhang et al. (2003), a prominent P300 was elicited when the pictures in the probe set were congruent with those in the memory set. A target-detection task experiment by Azizian et al. (2006) demonstrated that stimuli that were perceptually similar to the targets produced larger P300 responses than other stimuli. Furthermore, a recent study examined the neurophysiological process of brand extension with a prime-probe paradigm and found that a higher similarity and fit between the parent brand in the prime and the extension product in the probe resulted in a larger P300 amplitude (Ma et al., 2008). Thus, we hypothesized that if the brand logo extension could lead to a higher perceived fit than the brand name extension, then a larger P300 could be observed in the brand logo extension condition.

In the present experiment, we applied ERPs to investigate the neurophysiological process of the brand extension evaluation with two extension strategies (brand name extension and brand logo extension). The participants were presented combination pictures of the parent brand (name or logo) and the extension product. The evaluation of brand extension was measured by the subjects' acceptance (e.g., accept or not) according to previous works (Ma et al., 2008, 2014a). This study allowed us to explore which extension strategy (brand name extension or brand logo extension) enhanced the success of dissimilar brand extension and to deeply investigate the neurophysiological process underlying the brand extension evaluation.

METHODS

Participants

Sixteen right-handed students (nine males) aged 19–23 years (mean age = 21 years, $SD = 2.12$) from Zhejiang University participated in this experiment as paid volunteers. The students were all native Chinese speakers and had normal or corrected-to-normal vision. No participants reported a history of neurological disorder or mental disease. This study was approved by the institutional ethics committee of the Zhejiang University Neuromanagement lab. Written informed consent was obtained from all participants before the experiment was formally started. Data from one subject were discarded due to excessive recording artifacts, resulting in 15 valid subjects for the final data analysis.

Experimental Stimuli

In this experiment, the target stimuli were visual pictures of extension products with a parent brand. The size of each picture was 300 × 400 pixels. The brands consisted of five categories: beverage, food, clothing, vehicle, and technology (two brands per category). All brands were selected from the "Well-known Trademark List" published by the State Trademark Administration, China. The participants were all familiar with these brands, including Coca-Cola, Pepsi, and Nike, because they were selected in advance using a special Brand Familiarity Test. The brand was separately combined with the extension product using two brand identity signs (brand name and brand logo). The extension products comprised 20 products that belonged to different categories than the original product category of the parent brand.

Experimental Procedure

The subjects were comfortably seated in a dimly lit, sound attenuated, and electrically shielded room. The stimuli were presented centrally on a computer screen at a distance of 100 cm in front of the participant. A keypad was provided for the subjects to make their choices. The experiment consisted of 2 blocks, each containing 40 trials and lasting for about 3 min. During the experiment, the subjects were presented with 40 brand name extension tasks (BN) and 40 brand logo extension tasks (BL).

A stimulus system (Stim2, Neurosoft Labs, Inc., Sterling, VA, USA) was used to control the presentation of the stimuli. As illustrated in **Figure 1**, at the beginning of each trial a fixation appeared as a cue for 500 ms on the black screen, which was followed by an evaluation task to be performed. The evaluation task was presented for 1,000 ms and could be either a brand name extension evaluation or a brand logo extension evaluation. These evaluation tasks were randomized by the program, which made it impossible for the subjects to predict the type of upcoming task. During each evaluation task, the subjects were required to evaluate whether they would accept the presented product under the presented brand if it was sold in the marketplace. The subjects had a maximum of 2,000 ms to give their response by a button press. The response-to-hand assignments were counterbalanced across individuals. Each participant performed 10 practice trials before the start of the formal experiment.

EEG Recording

The electroencephalogram (EEG) was recorded (band-pass 0.05–100 Hz, sampling rate 500 Hz) from a set of 64 Ag/AgCl electrodes according to the 10–20 system with the Neuroscan Synamp2 Amplifier (Scan 4.3.1, Neurosoft Labs, Inc. Virginia, USA). The EEG electrodes were on-line referenced to the average

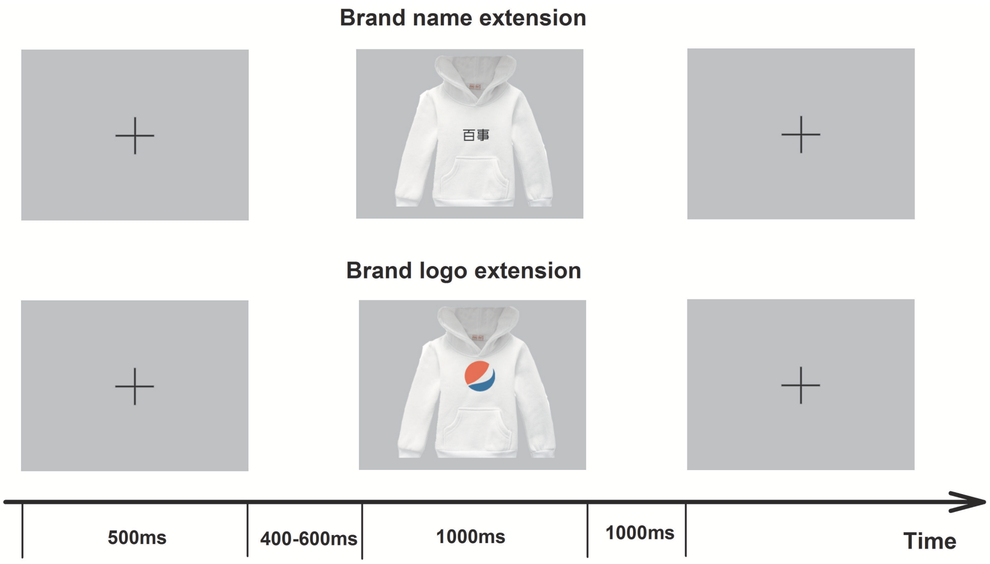

FIGURE 1 | Experimental task. The participants were presented with two strategies of brand extension (brand logo extension and brand name extension). They were instructed to accomplish the brand extension evaluation tasks and had a maximum of 2,000 ms to make their choice. EEGs were recorded from the subjects throughout the experiment.

of the left mastoid and later off-line referenced to the average of two mastoids. An electrode was applied to the cephalic location as the ground. Vertical electrooculograms (EOG) were recorded with one pair of electrodes placed on the supra-orbital and infra-orbital locations of the left eye, whereas the horizontal electrooculogram was recorded from electrodes on the outer canthi of both eyes. Electrode impedances were maintained below 5 kΩ throughout the experiment.

Data Analysis

For the analysis of the behavioral data, a paired t-test was adopted to compare the acceptance rates (AR) between the two brand extension conditions. The acceptance rate referred to the rate of like evaluations reported by the participants.

Ocular artifacts were removed during the offline EEG analysis. The EEG data were extracted from −200 to 800 ms time-locked to the onset of the task stimulus, with the pre-stimulus period used as the baseline. Electrooculogram artifacts were corrected using the method proposed by Semlitsch et al. (1986). Trials with peak-to-peak deflections exceeding ±80 μV and other artifacts were excluded. More than 35 sweeps for each condition remained, which are adequate to achieve stable and reliable measurements of N2 and P300 (Luck, 2005). The ERPs were averaged for every participant in both conditions (BN and BL). The averaged ERPs were digitally filtered through a zero phase shift (low pass at 30 Hz, 24 dB/octave).

According to previous studies on brand extension (Ma et al., 2007, 2008; Wang et al., 2012) and the scalp topographic distribution, nine electrode sites (F3, Fz, F4, C3, Cz, C4, P3, Pz, and P4) were selected for the data analysis. We averaged the ERPs amplitude of the 200–350 ms time window for the N2 component and the 400–600 ms time window for the P300 component. To study the neurophysiological features of the evaluation process on different brand extension strategies, a 2 (extension strategy) × 9 (electrode) within-subjects repeated measure ANOVA was conducted for the N2 and P300 components. The Greenhouse–Geisser (Greenhouse and Geisser, 1959) correction was applied when necessary, and the Bonferroni correction was used for multiple paired comparisons.

RESULTS

Behavior Results

The AR was 59.17% (SE = 3.41%) in the BL condition and 45.67% (SE = 4.47%) in the BN condition, which demonstrated a significant condition effect on the extension strategy [$t_{(14)} = 2.194$, $p < 0.05$; see **Figure 2**]. However, the response time in the BL condition was not significantly different with that in the BN condition [$t_{(14)} = -1.264$, $p > 0.05$].

ERPs Results

As presented in **Figure 3**, the ANOVA results for N2 showed main effects of extension strategy [$F_{(1,\ 14)} = 24.521$, $p < 0.001$, $\eta^2 = 0.637$] and electrode [$F_{(8,\ 112)} = 26.986$, $p < 0.001$, $\eta^2 = 0.658$]. The N2 amplitude elicited by the BN condition ($M = 1.66$ μV, SE = 0.96) was more negative than the N2 amplitude elicited by the BL condition ($M = 2.8$ μV, SE = 0.97). There was no significant interaction effect between the extension strategy and electrode [$F_{(8,\ 112)} = 0.541$, $p > 0.05$, $\eta^2 = 0.037$].

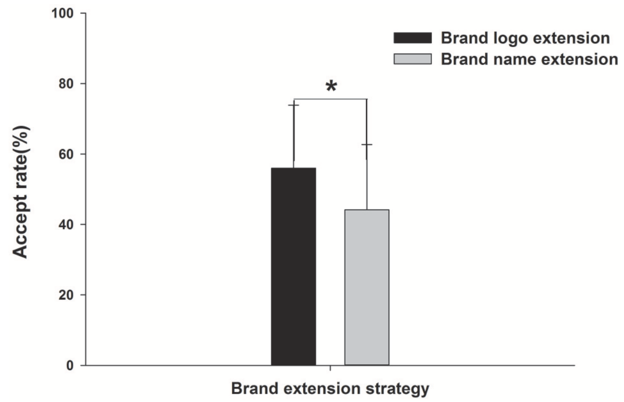

FIGURE 2 | Behavior results. Acceptance rates of the brand logo extension (BL) and brand name extension (BN) strategies. *$p < 0.05$.

For the P300 competent, the ANOVA produced significant main effects of the extension strategy [$F_{(1,\ 14)} = 7.198$, $p < 0.05$, $\eta^2 = 0.356$] and electrode [$F_{(8,\ 112)} = 11.420$, $p < 0.01$, $\eta^2 = 0.468$]. The mean P300 amplitude in the BL condition ($M = 6.80$ μV, SE = 1.26) was significantly larger than the mean P300 amplitude in the BN condition ($M = 5.25$ μV, SE = 1.25). The interaction effect was not significant [$F_{(8,\ 112)} = 0.786$, $p > 0.05$, $\eta^2 = 0.057$].

DISCUSSION

In the present study, we investigated how a consumer's perceived fit was influenced by different brand extension strategies (BN and BL) in the dissimilar brand extension evaluation process. Both the behavior and ERPs results demonstrated that the BL strategy could improve the perceived fit between parent brands and extension products compared to the BN strategy, which is the key to the success of brand extension. Regarding the subjects' behavior, we observed prominently higher acceptance under the BL strategy than under the BN strategy. During the neurophysiological process, a smaller N2 component and a larger P300 response were found in the BL strategy than in the BN strategy. Generally, we observed that extension products with parent brand logos showed a better perceived fit and were more favorable in the dissimilar brand extension when the subjects were shown evaluation tasks with different extension strategies.

A remarkable AR effect was found for the brand extension strategies (i.e., people showed a higher acceptance of the BL strategy than the BN strategy in the dissimilar brand extension evaluation process). As described in the Introduction, people tended to have a stereotype toward familiar brand information in their long-term memory that could lead to a better fit with the original product category but a worse fit with dissimilar product categories (Jin et al., 2015). In contrast, people's perceived fit between the unfamiliar brand information and the original product category was the same as the perceived fit between

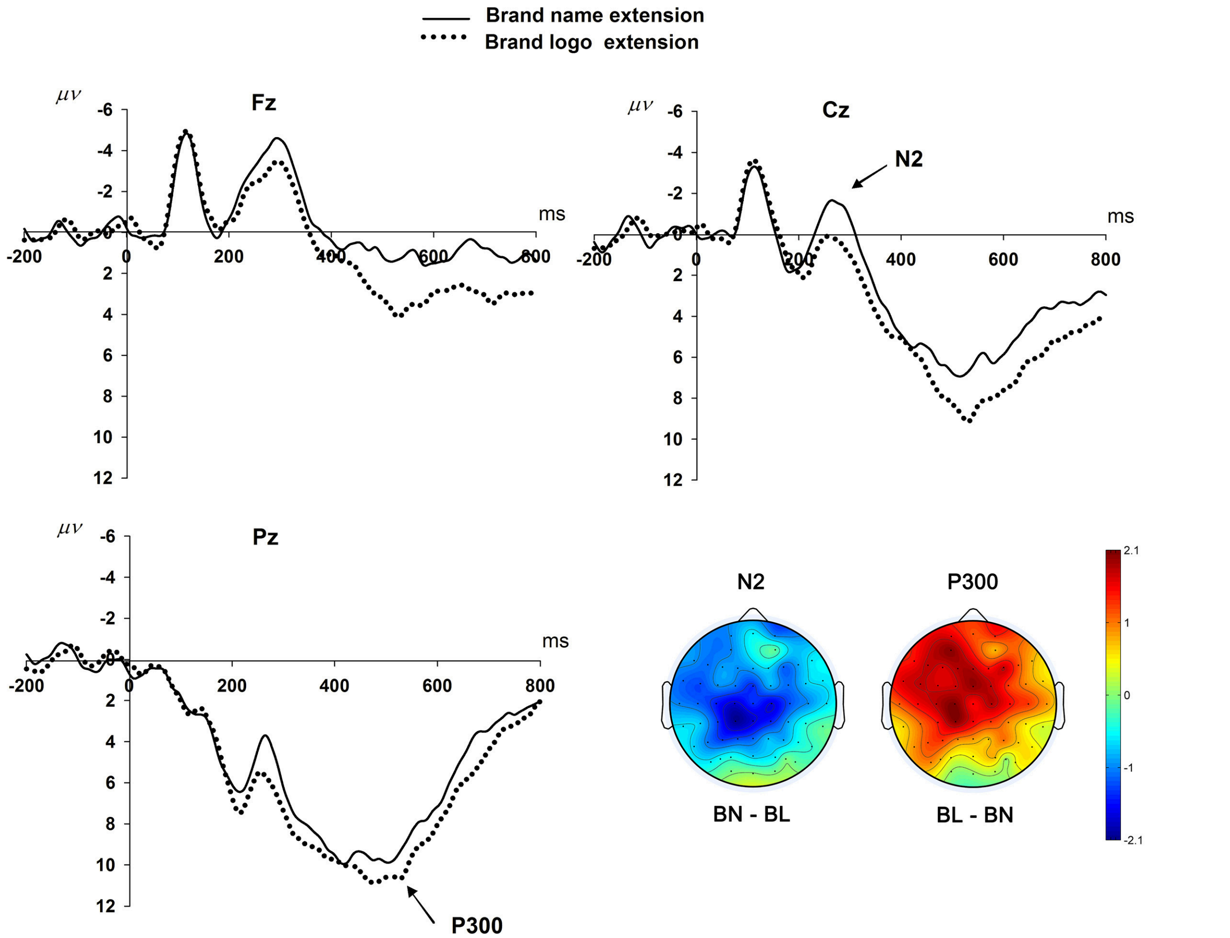

FIGURE 3 | ERPs results. Grand averaged ERPs of N2 and P300 elicited by the extension strategies (brand logo extension vs. brand name extension) from 3 midline electrodes in the forehead, central and parietal areas (Fz, Cz, and Pz). The scalp topographic distributions of the N2 (BN condition minus BL condition) and P300 (BL condition minus BN condition) are provided, and the bar for the topographic map ranges from −2.1 to 2.1 μV.

the unfamiliar brand information and the dissimilar product category because this unfamiliar information was not stored in the consumer's long-term memory (Jin et al., 2015). In the current study, brand names were more familiar information to consumers than brand logos and were stored in their long-term memory. As a result, brand names demonstrated a worse perceived fit with a dissimilar product category than brand logos. Thus, the BL strategy led to a higher perceived fit than the BN strategy. The higher perceived fit was related to a more positive extension evaluation (MacInnis and Nakamoto, 1990; Boush and Loken, 1991); hence, the BL strategy enhanced the acceptance of a dissimilar brand extension.

Regarding ERPs components, the N2 component reflects the conflicting information process (Van Veen and Carter, 2002; Folstein and Van Petten, 2008). As elaborated in the Section Introduction, a greater N2 amplitude would be observed when a conflict existed between S2 and S1 on either the physical attributes (Wang et al., 1998, 2004; Cui et al., 2000; Kong et al., 2000; Zhang et al., 2001; Yang and Wang, 2002; Mao and Wang, 2008; Han et al., 2015) or the brand perception (Ma et al., 2007, 2010). In the current study, brand names demonstrated a worse perception fit with the dissimilar product category than brand logos. Thus, the conflict between brands and products was larger for the BN strategy than the BL strategy, which was reflected on the enlarged N2 amplitude in the BN condition. However, this conflict effect was different from that reported in previous studies, which used a S1-S2 paradigm to examine the matching tasks (Wang et al., 1998, 2004; Cui et al., 2000; Kong et al., 2000; Zhang et al., 2001; Yang and Wang, 2002; Ma et al., 2007, 2010; Mao and Wang, 2008; Han et al., 2015). In these studies, the two stimuli (S1 and S2) were presented sequentially in the experiment. The information from S1 was first and temporarily encoded into the working memory system. When the information from S2 was transmitted into the brain, the temporary memory information from S1 was retrieved and compared with the information from S2. Then, the difference between S2 and S1 led to the temporary memory conflict and elicited the N2 component.

Thus, this type of conflict effect was attributed to a short-term memory conflict and could be considered a partial conflict. In contrast, in the current study, the S1 (brand) and S2 (product) stimuli were combined together into one stimulus and simultaneously presented to the subjects, which was closer to the actual marketing situation. In this case, the subjects evaluated the whole stimulus, retrieved the related information from their long-term memory, and then compared this whole stimulus with the long-term memory. The larger conflict between the two types of information led to a larger N2 amplitude. Therefore, this type of conflict effect was attributed to a long-term memory conflict, which could be considered as the whole conflict.

Following N2, a positive P300 component was found in the experiment. As elaborated in the Introduction, P300 represented the event categorization activity in the working memory, and a larger P300 amplitude would result in targets with higher similarity and coherence to the prior stimuli or to the working memory (Kok, 2001; Zhang et al., 2003; Azizian et al., 2006; Ma et al., 2008). In the current study, subjects had a stereotype toward brand name information that led to a better fit with the original product category in their long-term memory. Therefore, when the subjects were presented with a combination stimulus of a brand name and a dissimilar category product, they demonstrated a lower perceived similarity to the long-term working memory and the P300 amplitude was smaller. In contrast, people who did not have a stereotype toward brand logo information in their long-term memory exhibited a higher perceived similarity and P300 amplitude when they were presented with a combination stimulus of the brand logo and a dissimilar category product. Thus, in the present study, there was a pronounced P300 discrepancy in the evaluation process between the BL strategy and the BN strategy, indicating a higher perceived similarity between the BL strategy and the long-term working memory. This finding suggested that the extension strategy might be a significant influencing factor of perceived fit in the dissimilar brand extension evaluation process, thereby manifesting the categorization process in the working memory as reflected by the electrophysiological response of P300.

This study differed from traditional ERPs studies on brand extension in several major aspects. First, previous studies primarily used isolated word stimuli with the paradigm of S1(parent brand)-S2(extension product) to examine brand extension (Ma et al., 2007, 2008, 2010; Wang et al., 2012). For instance, in an experiment on a brand extension evaluation (Ma et al., 2007), sequential stimuli were displayed in a pair consisting of brand names (S1) and product names (S2), and a greater N270 amplitude was observed when the participants were presented with a stronger conflict between the brand category (S1) and the extension product category (S2). The recent study of Wang et al. (2012) used a similar paradigm with paired stimuli of brand names (S1)-product names (S2) but removed the conscious evaluation task on the brand extension. This approach elicited a larger N400 when the product's (S2) attributes were atypical to the brand category (S1), reflecting uncontrolled categorization processing (Wang et al., 2012). However, a drawback of these previous experiments was that the brands and the products were represented by words and appeared isolated from one another. As a result, prior to the evaluation process, the participants paid more attention to associate the two words of the stimuli together in their minds, which seriously influenced the regular evaluation process. In our current study, the target stimuli were direct physical pictures of extension products combined with the parent brand. This new paradigm and stimulus type are closer to the real marketing situation and help validly explore the brand extension evaluation process.

Second, we found that brand logo extension was another important extension strategy in addition to brand name extension and was a better strategy for dissimilar brand extension. The brand name extension strategy was primarily focused by previous researchers (e.g., Ma et al., 2008, 2010, 2014b; Wang et al., 2012; Jin et al., 2015). For example, in a brand name extension study by Ma et al. (2008), a pronounced P300 effect due to category similarity was demonstrated when subjects were required to evaluate the suitability of extending the parent brand name to a similar product category and a dissimilar product category. Ma et al. (2014b) suggested that a two-stage categorization process was involved in the evaluation of the perceived fit between the parent brand names and the extension products (Ma et al., 2014b). Jin et al. (2015) found that the association of a famous brand name with a dissimilar product category led to a worse acceptance than the strategy of new brand creation. However, in addition to this brand name extension strategy, brand logo extension is another important extension strategy because a brand can be identified by its brand logo as well as its brand name (Fombrun and Van Riel, 1997; Klink, 2003; Guzmán et al., 2012). In this study, the brand name is written in Chinese. Chinese is a special hieroglyphic language system. Chinese characters are derived from pictures representing meaning (Zhang et al., 2006). A previous ERPs study investigated the time course of brain activity for the English and Chinese characters. Chinese more quickly initiated processing of graphic form and more quickly shifted to processing of meaning than did English (Liu et al., 2003). Chinese characters are hieroglyphic or pictographic and their connections with meanings are more direct than other language systems (Lam et al., 2001; Liu et al., 2003; Zhang et al., 2006). It could be assumed that the cognitive perception of the brand name (in Chinese characters which is hieroglyphic) is not so different from that of a logo (symbol or sign which is graphical). But concerned about the brand extension, the brand logo or brand name is combined with the extension product. As the results showed, the cognitive perception of the name-product combination (BN) was so different from the logo-product combination (BL), which was reflected by a less negative N2 component and a larger P300 component in the BL than in the BN. It implied that the brand logo extension strategy would lead to an enhanced perceived fit in the dissimilar brand extension evaluation process. Thus, an additional contribution of the current study was the identification of a better strategy (i.e., brand logo extension) for dissimilar brand extension in marketing research.

CONCLUSIONS

To conclude, the current study explored which strategy [brand logo extension (BL) or brand name extension (BN)] better enhanced the success of dissimilar brand extension. Event-related potentials (ERPs) were used to investigate the electrophysiological process when subjects evaluated their acceptance of the brand extension. We found that the BL strategy increased the acceptance and perceived fit between parent brands and extension products compared to the BN strategy. In the neurophysiology process, this effect was reflected by a less negative N2 component and a larger P300 component in BL compared to BN. We suggested that N2 reflected a whole conflict between the brand-product combination and the long-term memory and that P300 could be regarded as the reflection of the categorization process in the working memory. Generally, these findings implied that the brand logo extension strategy would lead to an enhanced perceived fit in the dissimilar brand extension evaluation process. These findings are beneficial to future marketing studies.

ETHICS STATEMENT

This study was carried out in accordance with the recommendations of Neuromanagement laboratory's ethics committee in Zhejiang University with written informed consent from all subjects. All subjects gave written informed consent in accordance with the Declaration of Helsinki. The protocol was approved by the Neuromanagement laboratory's ethics committee in Zhejiang University. All participants had normal or corrected-to-normal vision. None of them reported any history of psychiatric or neurological disorders.

AUTHOR CONTRIBUTIONS

QS, XW, and GP conceived and designed the experiments. QS, SD, and XW performed the experiment. QS, GP, and SD analyzed the data. QS, GP, and XW wrote and refined the article.

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Inverted U-Shaped Curvilinear Relationship between Challenge and One's Intrinsic Motivation: Evidence from Event-Related Potentials

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The balance between task demand and one's competence is critical for the maintenance of intrinsic motivation. According to Flow theory and Self-determination theory, optimal challenge gives rise to the maximum intrinsic motivation, and an inverted U-shaped curvilinear relationship between perceived challenge and one's intrinsic motivation is suggested. In order to provide direct experimental evidences for predictions of these theories, in this study, we employed the two-player StopWatch game that we previously designed, which made references to the game format of a badminton tournament. According to our manipulation, a male participant was defeated by the same-sex player paired with him (played by a well-trained confederate of the experimenter) in two matches, one with a wide margin (the complete defeat condition) and another with a narrow one (the near miss condition). Participants performed better and reported to enjoy the near miss match to a greater extent. Besides, an enlarged Stimulus-preceding negativity was elicited when participants were actively anticipating outcomes in the near miss condition, suggesting greater anticipatory attention toward the outcome and an enhanced intrinsic motivation to win. Thus, converging electrophysiological evidences from this study and our former study confirmed the inverted U-shaped curvilinear relationship between perceived challenge and one's intrinsic motivation.

Keywords: optimal challenge, intrinsic motivation, flow, self-determination theory, event-related potentials, stimulus-preceding negativity

INTRODUCTION

To most human beings, competitive activities or games, sometimes even dangerous ones, have inherent appeal. Researchers from varied backgrounds have long been working on revealing the attractiveness of these activities. Pioneering investigations on the enjoyment of such activities as rock climbing and chess playing suggested intrinsic motivation to be derived from challenges, which are relatively difficult but are still within the participant's capacities and potential (Csikszentmihalyi, 1975). A recent study reported that outcome uncertainty and suspense accompanied by challenges greatly influenced one's intrinsic motivation. Compared with the game in which one outperformed his or her opponent by a wide margin, the close game led to greater enjoyment and enhanced intrinsic motivation (Abuhamdeh et al., 2015). Combining these results, it is suggested that people tend to get most pleasure in optimally challenging activities, which implies an inverted U-shaped curvilinear relationship between challenge and intrinsic motivation. Accordingly, before the apex of the U-shaped curve is reached, the increasing of one's confronted challenge should lead to increase in the intrinsic motivation level. Afterwards, further increasing of one's confronted challenge should lead to decrease in one's intrinsic motivation instead.

The optimal level (i.e., the apex of the curve) is named as flow in Flow theory, which is described as an intrinsically motivating and fully engaging state of consciousness (Csikszentmihalyi, 1990). Flow theory highlights the importance of optimal challenges for sake of enjoyment, which refers to challenges balanced with one's skills (Csikszentmihalyi, 1975). Specifically, flow's dynamic structure of the perceived match between personal skill and challenge has been divided into three different channels: flow (balanced skill and challenge), boredom (high skill vs. low challenge), and anxiety (low skill vs. high challenge; Csikszentmihalyi and Rathunde, 1993). In fact, the postulate of optimal challenge is consistent with the competence need described in the Self-determination theory (SDT; Deci and Ryan, 1980). In terms of SDT, the basic psychological need of competence is defined as feeling skilled, capable or effective in interactions within a given environment, which is suggested to be a key source of one's intrinsic motivation (Deci and Ryan, 1980, 1985). As a consequence, optimal challenge, compared with a lack of challenge and overwhelming challenge, maximizes one's perceived competence and then enhances one's intrinsic motivation to win.

While mainstream motivation theories give consistent predictions regarding the role of optimal challenge in boosting intrinsic motivation (Csikszentmihalyi, 1975; Deci and Ryan, 1980), direct experimental evidences in support of flow's dynamic structure and more specifically, the inverted U-shaped curvilinear relationship between challenge and intrinsic motivation are still relatively rare. In our previous study (Meng et al., 2016), we developed a two-player StopWatch (SW) game adopting the game format of a badminton tournament. We made sure that a male participant defeated the male confederate of the experimenter (hereafter referred to as "confederate") paired with him in two matches, one with a wide margin (blowout: the lack of challenge condition) and another with a narrow one (narrow win: the optimal challenge condition). Because intrinsic motivation was difficult to be measured in an objective manner, electroencephalograms (EEGs) were recorded throughout the task and event-related potentials (ERPs) were employed to track one's intrinsic motivation. During the outcome anticipation stage, we observed an enlarged Stimulus-preceding negativity (SPN) in the optimal challenge condition, suggesting that participants formed greater anticipation toward the outcome and were more intrinsically motivated to succeed during close games. To the best of our knowledge, our previous study was the first neuroscientific investigation of Flow theory, which validated the important role of optimal challenge in promoting one's intrinsic motivation (Meng et al., 2016). However, it is worth noting that, our previous study only revealed one side of the coin, as participants finally won in both rounds and felt competent in the end (that is, before the apex of the U-shaped curve is reached). Then what will happen if participants failed in the end and felt incompetent instead? Will perceived challenge still play a role in modulating one's intrinsic motivation in this situation (that is, after the apex of the U-shaped curve has been reached)? This open question remained to be settled.

People often have the experience that they are so close to winning a game or obtaining a reward, only to lose it in the end. In this kind of close game, challenges confronted by people are beyond the skills they obtained by a narrow margin. Compared with completely losing control of the game, this situation may induce a stronger feeling of competence, as well as the experience of flow. Given that optimal challenge is significant for the experience of flow even if people do not manage to win in the end, we would like to compare one's intrinsic motivation between the near miss condition and the complete defeat condition in the controlled laboratory setting. As games are goal directed and competitive in nature (Song et al., 2013), they provide an interesting venue to test our hypotheses. In this study, we engaged participants in the same online SW game derived from Meng et al. (2016), in which each participant was paired with a same-sex confederate. Different from our previous study in which participants won both rounds of the game (Meng et al., 2016), the well-trained confederate won both rounds in this study. In order to manipulate the two challenge levels, the confederate won a round of game with a wide margin while won the other round with a narrow one.

As was done in previous studies (Ma et al., 2014; Jin et al., 2015), EEGs were recorded during the experiment in order to clarify the temporal dynamics of motivational processes. The SPN is a sustained, negative shift in potential that mirrors the anticipation of a motivational stimulus during the pre-feedback period (Brunia, 1988; Böcker et al., 1994; Donkers et al., 2005; Masaki et al., 2010). It typically shows right-hemisphere preponderance and usually maximizes over right prefrontal cortex (for a recent review, see Brunia et al., 2012). Previous studies demonstrated that a larger SPN indicated an enhanced expectation toward the outcome and intensified intrinsic motivation toward the task (e.g., Kotani et al., 2015; Meng and Ma, 2015; Meng et al., 2016; Wang et al., 2017). In the current research, the near miss condition of the game provides optimal challenge compared with the complete defeat condition, which bears more motivational relevance to participants and is predicted to be more intrinsically motivating and engaging. Thus, we assume that participants will form greater anticipation toward feedback during the near miss match, resulting in an enlarged SPN.

A potential limitation of our previous study is that we neglected to collect subjective data, which may serve to support our electrophysiological findings (Meng et al., 2016). To address this limitation, after the formal experiment, participants were asked to report their enjoyment level, effort expended as well as the extent they cared about task performance for each round of the game. Ryan et al. (2006) suggested that one's intrinsic motivation was significantly associated with enjoyment. It was also found that optimal challenge can result in more attention devoted, greater persistence and determination (Aubé et al., 2014). Thus, we predict participants to enjoy more, invest greater effort and care more about task performance in the near miss condition. As to the task performance, previous studies consistently argued that intrinsic motivation plays a significant role in producing adaptive outcomes (e.g., Aubé et al., 2014; Cerasoli and Ford, 2014). For instance, by measuring the perception of time in the computer games, it was found that participants had a greater intrinsic motivation and performed better in the adaptive playing mode than in the overload condition (Keller and Bless, 2008). Thus, we predict participants to be more committed to experimental tasks and to perform better in the near miss condition.

METHODS

Participants

A total of 20 right-handed male graduate and undergraduate students participated in this study, ranging in age from 20 to 25 years ($M = 21.75$, $SD = 1.37$). They were all native Chinese speakers, had normal or corrected-to-normal vision, and did not have any history of neurological disorder or mental diseases. This research was approved by the Neuromanagement Lab Ethics Committee at Zhejiang University, and all participants provided written informed consent before the experiment. A male experimenter acting as the confederate was matched with male participants as pairs to take part in the formal experiment. Data of two participants were discarded because at least one of the experimental conditions were unsuccessfully manipulated. Thus, there were eighteen valid participants for the final analysis.

Stimuli and Procedure

Before the experiment, the participant was briefly introduced to his co-player (the confederate) face-to-face. Then experimental environment and facilities unfamiliar to participants were introduced. We strictly tracked these procedures to make the participants believe in the authenticity of the two-player online game. After that, the two players were led to take seats in separate rooms which are dim, sound-attenuated and electrically shielded. Experimental stimuli were presented on the computer screen at a distance of 100 cm away from subjects, with a visual angle of $7.50 \times 5.40°$. Stimuli, recording triggers, and response data were presented and recorded by E-Prime 2.0 (Psychology Software Tools, Pittsburgh, PA, USA). Participants were instructed to use the keypad to complete SW tasks all along.

SW game was adopted as the experimental task. In the traditional single-player SW game, a stopwatch would automatically start and the player should try his/her best to stop the watch around a specific time point (Murayama et al., 2010; Ma et al., 2014). In one of our previous studies, we designed an interactive online SW game involving two players (Meng et al., 2016). Between the two players, whose response appears closer to 3 s wins the trial and gets one point. Importantly, game format of the badminton tournament was integrated in this game. In other words, the player who accumulates 21 points first and obtains at least 2 more points than his counterpart wins that round of the match. The same rule was adopted in this study (See **Figure 1**).

As illustrated in **Figure 2**, in each trial, a fixation appeared at the very beginning for 1,000 ms. Then, players had to wait for 600–800 ms before the watch automatically started running. After the watch started running, each player could stop it by pressing any of the appointed buttons. If a player pressed the button earlier, he had to wait for the other player to respond. After both players responded, a blank with black background appeared for 1,200 ms. In the end, their performance and the outcome (belongingness of the point) were shown for 1,200 ms. For the player who won, one point would be added, and his performance would be shown in green. The other one would gain no point in this trial and the score would appear in red. If two players responded equally close to 3 s, no one would gain a point and their performance would be shown in black. What's more, the accumulated points would appear on the top of each watch.

For each participant, there were a total of two rounds (blocks) of SW games. During each round, the game would continue until there is a winner. Sequences of experiment conditions (near miss vs. complete defeat) were counterbalanced between participants.

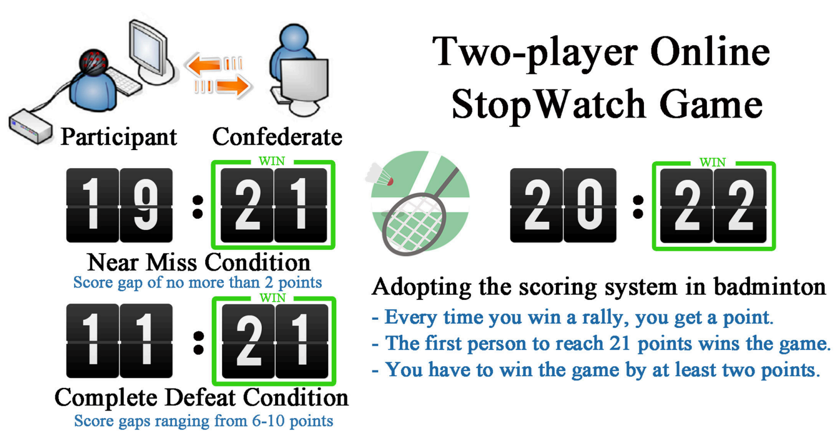

FIGURE 1 | Game format of the two-player online StopWatch Game.

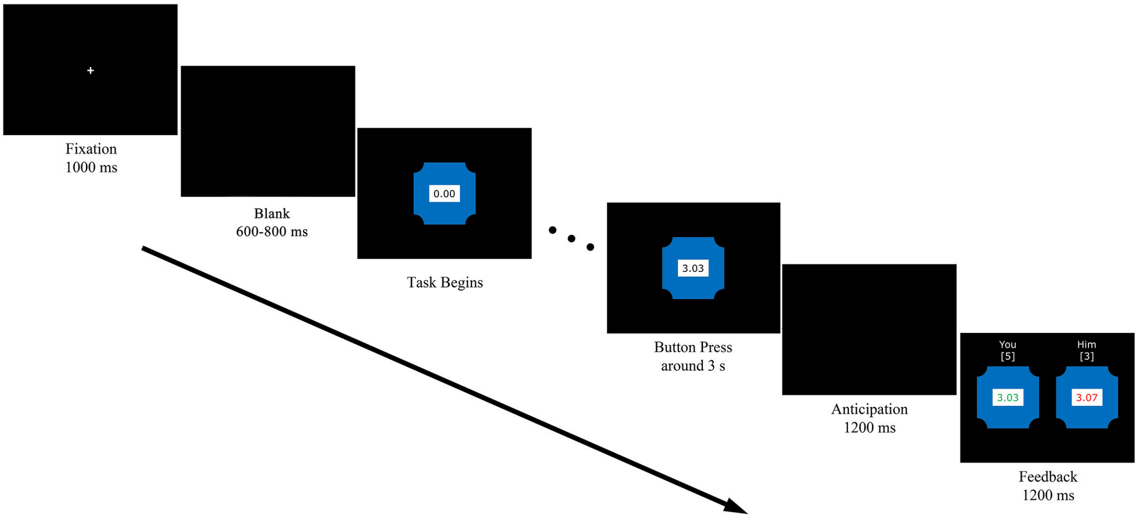

FIGURE 2 | Illustration of the experimental stimuli applied in a single trial.

For half of them, the first round was set to be a near miss game. Each round of match (a block) contains a minimum of 32 trials (for the complete defeat condition) and a maximum of 50 trials (for the near miss condition). The experimenter who played as the confederate was sufficiently trained and was very good at playing the SW game. In a near miss round, scores of the two players should rise alternatively and the confederate should never accumulate more than 2 points relative to the participant. He should also make sure that the participant lost this round at the last minute. If a round was set to be a complete defeat, the confederate should make sure that he could open the scoring. The score gap gradually widened and the confederate finally won the round with an enormous advantage ranging from 6 to 10 points (as shown in **Figure 1**). On the extreme case that some of the designs were not successfully manipulated, the data of the involved participant would be discarded. In our study, data of two participants were discarded because of the unsuccessful manipulation.

Prior to the initiation of the formal experiment, each player can practice our single-player version of the SW game for 10 rounds to familiarize themselves with the procedure. They were also informed that they would receive ¥ 35 as compensation for their time and participation, and that their task performance was not related to the final payoff. Thus, participants were intrinsically motivated to win the game rather than to win extra money. After the formal experiment, the participant was asked to report their enjoyment level, effort expended as well as the extent they cared about task performance for each block of the game (from 1 = "the least" to 5 ="the greatest").

EEG Data Acquisition and Analysis

EEG was recorded (band-pass 0.05–70 Hz, sampling rate 500 Hz) with Neuroscan Synamp2 Amplifier (Scan 4.3.1, Neurosoft Labs, Inc. Virginia, USA). The elastic electrode cap with 64 Ag/AgCl electrodes was used in accordance with the standard international 10–20 system. A frontal electrode site between FPz and Fz was used as the ground. There were two mastoid electrodes and the left one was used as a reference. Horizontal and vertical electrooculograms (EOG) were monitored with two pairs of electrodes. One pair was located below and above the left eye in parallel with the pupil and the other pair was placed 10 mm from the lateral canthi. The experiment got started only after the electrode impedances were reduced to under 5 kΩ.

In off-line analysis, the EEG data were re-referenced to the algebraically computed average of the left and right mastoids for further analysis. The EOG artifacts with ocular movements were corrected using the method proposed by Miller et al. (1988). The EEGs were digitally low-pass filtered at 30 Hz (24 dB/Octave) and were segmented into epochs from −1,000 ms to feedback onset, with the activity from −1,000 to −800 ms serving as the baseline. Trials that contained amplifier clipping, bursts of electromyography activity, or peak-to-peak deflections that exceeded ±80 μV were excluded from the final averaging procedure. More than 30 sweeps remained for each condition, which are adequate to achieve stable and reliable measurements of typical ERP components (Luck, 2005). The EEG epochs were averaged separately for each condition. Specifically, they were averaged for the complete defeat condition (all trials within the block in which the participant lost with a wide margin) and the near miss condition (all trials within the block in which the participant lost with a narrow margin).

Statistical Analysis

For the behavioral data analysis, since the player whose response was closer to 3 s won the trial, mean absolute deviation around the central point (3 s) was calculated for each condition and a paired t-test was used to compare the means. In addition, paired t-tests were adopted to compare the means of self-reported enjoyment level, effort expended as well as the extent participants cared about task performance. For the EEG analysis,

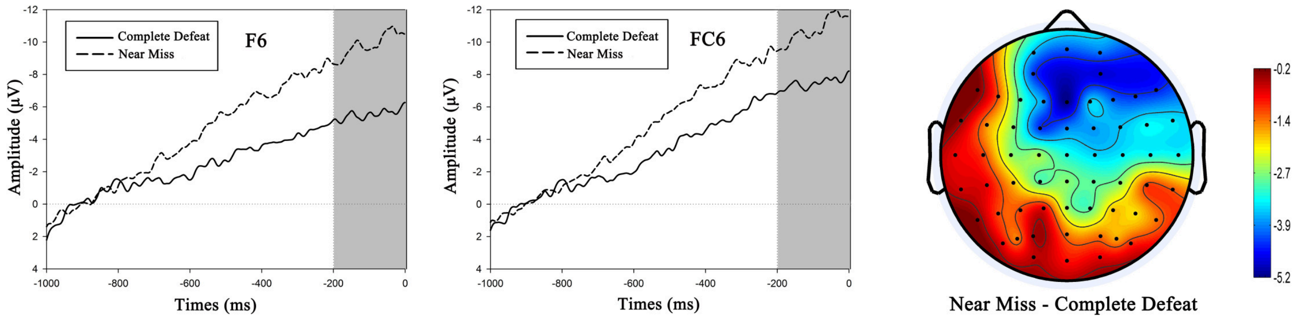

FIGURE 3 | SPN results during the anticipation stage. For illustration, grand-average ERP waveforms of SPN from two representative electrodes (F6, FC6) are demonstrated. The scalp topographic distribution of SPN is provided (amplitude in the near miss condition minus that in the complete defeat condition), and the bar ranges from −5.2 to −0.2 μV.

according to scalp topography of this study (see **Figure 3**) as well as previous studies (Van Boxtel and Böcker, 2004; Brunia et al., 2011; Meng et al., 2016), SPN has an anterior distribution and typically shows right-hemisphere preponderance. Thus, SPN amplitudes from the electrodes F4, F6, F8, FC4, FC6, and FT8 were analyzed. Mean amplitudes from −200 to 0 ms prior to feedback onset went into a within-subject 2 (challenge level) × 6 (electrode) repeated-measures analysis of variance (ANOVA). The Greenhouse–Geisser correction was applied in all statistical analyses when necessary (Greenhouse and Geisser, 1959).

RESULTS

Behavioral Results

For the behavioral results, the mean absolute deviation was 0.103 s for the complete defeat condition and was 0.079 s for the near miss condition. The two means were significantly different from each other [$t_{(17)} = 3.578$, $p = 0.002$]. Results of the paired comparisons between subjective data collected from the near miss condition and the complete defeat condition were shown in **Table 1**.

TABLE 1 | Means of ratings and pair comparisons.

Variables	Near miss condition	Complete defeat condition	*T*-test results
Enjoyment	4.056	3.667	$t_{(17)} = -3.289$, $p = 0.004$
Effort	4.667	3.889	$t_{(17)} = -5.102$, $p < 0.001$
Concern about task performance	3.833	3.222	$t_{(17)} = -4.267$, $p = 0.001$

ERP Results

For the 2 (challenge level: near miss vs. complete defeat) × 6 (electrode: F4, F6, F8, FC4, FC6, and FT8) repeated measures ANOVA of SPN, the results showed a significant main effect of challenge level [$F_{(1, 17)} = 20.315$, $p < 0.001$, $\eta^2 = 0.544$]. The near miss condition ($M \pm SE$, -8.957 ± 0.987 μV) induced a significantly more negative SPN than the complete defeat condition ($M \pm SE$, -5.488 ± 0.754 μV; as shown in **Figure 3**). The main effect of electrode was also significant [$F_{(5, 85)} = 2.601$, $p = 0.031$, $\eta^2 = 0.133$]. Nevertheless, the interaction between challenge level and electrode was not significant [$F_{(5, 85)} = 0.730$, $p = 0.603$, $\eta^2 = 0.041$].

DISCUSSION

Starting from Flow theory and SDT (Csikszentmihalyi, 1975; Deci and Ryan, 1980), this study investigates how the fit between participants' competence and the task demand affects intrinsic motivation. Specifically, intrinsic motivation was examined in the near miss condition and the complete defeat condition of the two-player online SW game. In line with our hypotheses, participants reported to enjoy the near miss round more, and the SPN was more pronounced in the near miss condition.

Pioneering studies demonstrated that SPN reflected the expectancy of a motivational stimulus during the pre-feedback period (Böcker et al., 1994; Donkers et al., 2005; Masaki et al., 2010; Meng and Ma, 2015; Meng et al., 2016; Wang et al., 2017). As the one who has a stronger intrinsic motivation to win would generally care more about the outcome and be more closely anticipating the feedback, and the enhanced subjective expectancy toward feedback would elicit a more prominent SPN, the SPN was suggested as an electrophysiological indicator sensitive to the motivation level (Brunia et al., 2012; Kotani et al., 2015; Meng et al., 2016). In this research, a larger SPN was observed during the feedback anticipation period of the near miss condition. As participants received fixed payoffs irrelevant to task performances, this finding suggested that participants were more intrinsically motivated to win in close games.

According to Flow theory (Csikszentmihalyi, 1975), participants get to experience flow when demands of the task are in balance with their capacities. Too much challenge, which is beyond individuals' capacities, will lead to anxiety and disengagement. In line with Flow theory, in SDT Deci and Ryan (1985) put forward that intrinsically motivated behaviors are partially based in people's needs to feel competent. SDT differentiates the content of outcomes and the processes through which the outcomes are pursued. Although participants lost both rounds of the game, the process in the near miss condition was quite different from that in the complete defeat condition. In the complete defeat condition, the score gap rapidly widened and the participant fell far behind. This dynamic would lead to perceived incompetence, which tends to undermine intrinsic motivation (Deci and Ryan, 2000). It may also lead to weaker self-efficacy and negative mood (Song et al., 2013). As a result, participants were more likely to lose focus and might incline to give up in the end. To the participants, a balanced status was approached between their competence and confronted challenge in the near miss condition relative to the complete defeat condition. Although the participant still fell behind on the whole, they faced a close race with his opponent and their scores rose alternately. Accordingly, they were more likely to be intrinsically motivated and to keep a close eye on their task outcomes throughout the round of the game.

Based on Flow theory and SDT, there may be an inverted U-shaped curvilinear relationship between challenge and intrinsic motivation (Csikszentmihalyi, 1975; Deci and Ryan, 1980). It suggests that increase in challenge should lead to an increase in one's intrinsic motivation up to the apex of the curve, while further increase in challenge would lead to a decrease in one's intrinsic motivation. Meng et al. (2016) suggested the important role of optimal challenge in promoting one's intrinsic motivation to win and provided neural evidence for the validity of the left half of the curve. To be specific, electrophysiological results suggested that participants formed greater anticipatory attention toward feedback and were more intrinsically motivated to win in the narrow win condition compared with during the blowout. In this follow-up study, we gave additional neural evidence for the validity of the curve's right hemisphere (near miss and complete defeat conditions). It is worth noting that dynamics of the narrow win condition in our previous study (Meng et al., 2016) and the near miss condition in this study are highly similar. In both conditions, scores of the participant and the confederate would rise alternatively. The only difference between the two conditions was the belongingness of the winner. Since we tracked the electrophysiological representation of intrinsic motivation during the game (before there is a winner for the round) rather than after the outcome has been determined, the final outcome would not influence one's intrinsic motivation during the game. Thus, both conditions provided optimal challenge to the participants and we deem them to be intrinsically motivated to a similar extent in the two conditions.

Combining electrophysiological results from this study and our previous study (Meng et al., 2016), the inverted U-shaped curvilinear relationship between perceived challenge and one's intrinsic motivation gets validated, and we can conclude that people were indeed most intrinsically motivated in optimally challenging activities. As depicted in **Figure 4**, challenge is defined as the independent variable, while one's intrinsic motivation is defined as the dependent variable. To be specific, challenge is a nominal variable (1 = blowout, 2 = narrow win, 3 = near miss, and 4 = complete defeat), and we resorted to the mean amplitude of SPN from the six selected electrodes (F4, F6, F8, FC4, FC6, and FT8) to describe one's intrinsic motivation. Through curve fitting, we got an inverted U-shaped fitting curve and a polynomial function ($y = 2.022x^2 - 10.406x + 3.854$).

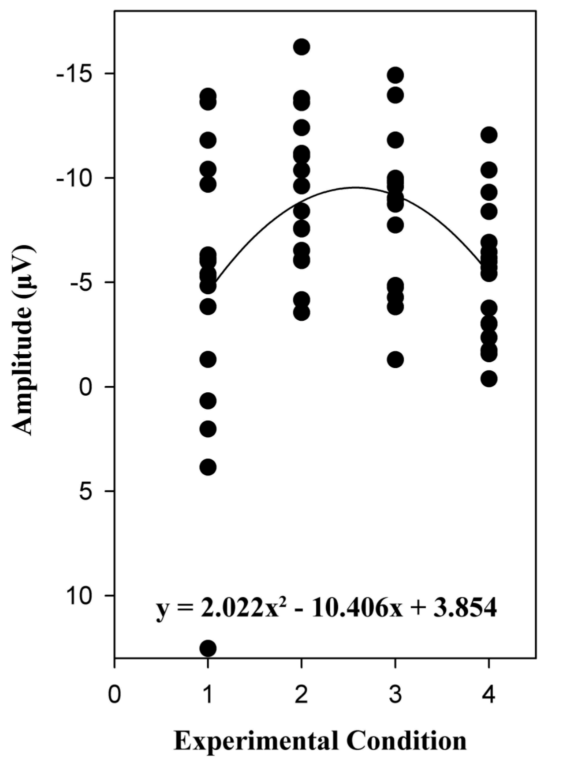

FIGURE 4 | Verification of the inverted U-shaped model based on electrophysiological results from this study and Meng et al. (2016).

From **Figure 4**, we can see that only when participants perceived a good match between task skill and confronted challenge (narrow win and near miss conditions) would they experience flow (Csikszentmihalyi and Rathunde, 1993). In fact, similar phenomena can be observed in varied domains. For instance, a cellular level neurophysiological study suggested an inverted-U effect to dopamine D1 receptor (D1R) on prefrontal cortex (PFC) neuronal firing (Vijayraghavan et al., 2007). As a consequence, while spatial working memory gets enhanced by moderate D1R stimulation, it gets impaired by either too little or too much of D1R stimulation.

Across different domains, previous studies have consistently argued that there is a significant role for intrinsic motivation in producing adaptive outcomes (e.g., Keller and Bless, 2008; Aubé et al., 2014; Cerasoli and Ford, 2014). To be specific, it was found that optimal challenge can lead to more attention devoted, greater persistence and stronger determination, all of which are beneficial to the improvement of task performance (Aubé et al., 2014). For instance, Keller and Bless (2008) found that participants in the adaptive playing mode condition reached higher scores on the task than in the overload condition. As a complement to our electrophysiological finding, participants performed better in the near miss condition, and the mean absolute deviation from 3 s in the near miss condition was significantly smaller than that in the complete defeat condition. Besides, participants reported to enjoy the game to a greater extent, to throw more effort into the game and to care more about their task performance in the near miss condition. Taken together, these results suggest that participants feel optimally challenged and more confident in the near miss condition, which make them more committed to experiment tasks even without foreseeable positive results and thus achieve better task performances (Shernoff et al., 2003).

Lab experiments have rigorous restrictions on the experimental design, and it is quite difficult to simulate real-life activities (Meng et al., 2016). However, the design of a two-player online SW task, with a game format similar to the badminton tournament, can not only easily manipulate the challenge level but also arouse participants' inner or "real" feelings in controlled laboratory settings, which is a major contribution of our studies. Besides, this study also has empirical implications. "Gamification", which applies game elements and design techniques to training and learning programs, has been commonly suggested to effectively facilitate one's enjoyness and flow experience during the target activity (Studer and Knecht, 2016). Adopting this approach, motivation-enhancing elements of the two-player online SW game (e.g., moderate competition) can be elaborately integrated into daily activities. Intrinsic motivation in doing these activities would get strengthened, while original formats of them may keep intact. Another point worth mentioning is that we resorted to ERPs to represent one's intrinsic motivation level. Existing studies on intrinsic motivation mainly relied on established scales. However, self-report itself is highly subjective in nature and may bring observable biases and large variation (Camerer, 2010; Meng et al., 2016). As SPN has been recommended as a neural indicator of one's motivation level (Kotani et al., 2015; Meng and Ma, 2015), we integrated physiological and subjective evidences to achieve a more objective measurement of intrinsic motivation.

CONCLUSION

To sum up, in this research we employed the two-player SW game that we previously designed, the game format of which is similar to that of a badminton tournament. Two experimental conditions were cautiously manipulated so that real participants were defeated by a same-sex experimenter with a wide margin in one match (complete defeat) and with a narrow margin in another one (near miss). Converging behavioral and electrophysiological evidences suggested that participants fostered a greater intrinsic motivation to win in the near miss condition. Combined with findings of our previous study (Meng et al., 2016), the inverted U-shaped curvilinear relationship between confronted challenge and one's intrinsic motivation was validated.

ETHICS STATEMENT

This study was carried out in accordance with the requirements of the Neuromanagement Lab Ethics Committee at Zhejiang University. All subjects gave a written informed consent according to the Declaration of Helsinki. All participants had normal or corrected-to-normal vision. None of them reported any history of psychiatric or neurological disorders.

AUTHOR CONTRIBUTIONS

LM and GP conceived and designed the experiment. GP and LM performed the experiment. GP and LM analyzed and interpreted the data. GP, LM and QM wrote and refined the article.

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Who Deserves My Trust? Cue-Elicited Feedback Negativity Tracks Reputation Learning in Repeated Social Interactions

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Trust and trustworthiness contribute to reciprocal behavior and social relationship development. To make better decisions, people need to evaluate others' trustworthiness. They often assess this kind of reputation by learning through repeated social interactions. The present event-related potential (ERP) study explored the reputation learning process in a repeated trust game where subjects made multi-round decisions of investment to different partners. We found that subjects gradually learned to discriminate trustworthy partners from untrustworthy ones based on how often their partners reciprocated the investment, which was indicated by their own investment decisions. Besides, electrophysiological data showed that the faces of the untrustworthy partners induced larger feedback negativity (FN) amplitude than those of the trustworthy partners, but only in the late phase of the game. The ERP results corresponded with the behavioral pattern and revealed that the learned trustworthiness differentiation was coded by the cue-elicited FN component. Consistent with previous research, our findings suggest that the anterior cue-elicited FN reflects the reputation appraisal and tracks the reputation learning process in social interactions.

Keywords: trustworthiness, trust game, social learning, event-related potential, feedback negativity

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INTRODUCTION

In many social interactions involving exchanges, trust and trustworthiness are essential components because social exchange relationship usually develops on trust where formal contracts are absent (Ashraf et al., 2006). Trust and trustworthiness foster reciprocity and pro-social behaviors and contribute to better economic outcomes on both individual and organizational levels (Charness et al., 2011; Johnson and Mislin, 2011).

In general, one trusts another because the latter is believed to be trustworthy. The strength of this belief is affected by various factors of the two parties. Studies have shown that one's gender, race and socioeconomic status influence how much she/he trust others (Alesina and La Ferrara, 2002; Chaudhuri and Gangadharan, 2007). It is also found that the level of trust is different among different countries and regions (Willinger et al., 2003; Johnson and Mislin, 2011). One's trustworthiness, as perceived by the partner in their interaction, can be affected by her/his gender (Slonim and Guillen, 2010), ethnicity or nationality (Glaeser et al., 2000; Fershtman and Gneezy, 2001), and multiple facial characteristics or expressions (Scharlemann et al., 2001; DeBruine, 2002; Campellone and Kring, 2012; Chen et al., 2012; Giang et al., 2012; Tortosa et al., 2013; Sofer et al., 2015). On the other hand, people often rely on prior social information, i.e., reputation, to infer the trustworthiness of the current partner (Delgado et al., 2005; Bracht and Feltovich, 2009; Chang et al., 2010; Charness et al., 2011; Fouragnan et al., 2013).

More often and more importantly, people assess trustworthiness by observing the behavior of a social partner in their interactions, especially in repeated interactions. This is an "interaction-based" learning process (Fouragnan et al., 2013) in which a trustor learn the trustee's reputation through experience with her/him. To study this type of interactions, researchers in social decision making utilize a well-developed paradigm called the trust game that was first designed by Berg et al. (1995) (BDM trust game). The initial BDM trust game was a one-shot game between two anonymous persons. The trustor was first endowed with $10 and then decided how much to "invest" to the trustee. The amount invested was tripled and finally the trustee decided how much to pay back. Contrary to traditional economic theories, studies revealed that the trustor often invested and the trustee also paid back (Berg et al., 1995; Johnson and Mislin, 2011). It is suggested that this game measures trust and trustworthiness (Bracht and Feltovich, 2009). To address trust evolving and trustworthiness learning, studies have adopted the repeated version of the trust game that has a better ecological validity. Behavior studies, including those using mathematical models, have attempted to describe the reputation formation and learning dynamics during the repeated trust game (Anderhub et al., 2002; Cochard et al., 2004). These studies implicitly suggest that the strategies of both parties in the game follow the premise that the trustors make decisions based on the trustworthiness observed from the trustees' behavior. There are also experiments manipulating the trustees' trustworthiness and focusing on how the trustees' behavior affected the trustors' decisions in multi-round trust games (Chang et al., 2010; Campellone and Kring, 2012). They found that a trustor's experience with the partner updated her/his belief of the partner and the subsequent decision. Moreover, this experience-based reputation overrode other social signals such as the partners' facial trustworthiness or facial emotions.

Evaluation of trustworthiness with various kinds of information has also been investigated by neuroscience research. A number of studies have reported the neural representation of trustworthiness appraisals that were solely based on facial characteristics when previous social interactions were absent. While most of these studies used lesion and functional magnetic resonance imaging (fMRI) methods (Adolphs et al., 1998; Winston et al., 2002; Engell et al., 2007; Todorov et al., 2008; Castle et al., 2012; Mattavelli et al., 2012; Freeman et al., 2014), only a few event-related potential (ERP) studies have observed the electrophysiological correlates of trustworthiness evaluation when subjects saw different faces. Yang et al. (2011) explored subjects' ERP time course during a simple evaluation task where they rated the facial trustworthiness of pre-categorized faces. The effects of facial trustworthiness on the earliest evoked visual component C1 (40–90 ms) and the late positive components (LPC, 400–600 ms) amplitudes were found in this study. Furthermore, only the LPC amplitude was found to be associated with subjective trustworthiness rating in the task. The authors attributed the C1 effect to the structural facial properties conveying cues about trustworthiness, while the trustworthiness effect on the LPC was interpreted as the attentional, affective or motivational aspects of facial trustworthiness processing. Another study also looked into the ERP differences between trustworthy and untrustworthy faces in a similar rating task (Marzi et al., 2014). The ERP components whose amplitudes varied with different subjective trustworthiness rating included the P100 (110–130 ms), an early posterior negativity (EPN, 200–350 ms) and the late positive potential (LPP, 300–500 ms). All of these components exhibited more pronounced amplitudes for subjectively rated untrustworthy compared to trustworthy faces. However, amplitudes of these components did not differ between different pre-experimental rated trustworthiness face categories. In another study where trustworthy or untrustworthy faces selected based on consensus judgments were paired with positive or negative personality traits, subjects' ratings on the faces' trustworthiness were affected by both perceptual and learned information (Rudoy and Paller, 2009). The ERP results suggested that perceptual information processing during trustworthiness appraisal was correlated with earlier (200–600 ms) ERPs in the anterior frontal sites while the effect of remembered information on this appraisal could be identified in a later (800–1000 ms) ERP correlate in the parietal sites. Although inconsistency remains among these three studies, it can be implied that during simple facial trustworthiness appraisal, earlier ERP components are associated with the rapid perception of certain physical facial characteristics embedding trustworthiness information. Later components, on the other hand, underlie more deliberate and emotional/motivational processing.

There is also literature regarding trustworthiness assessment and reputation learning during social interactions such as games and their neural bases. It has been demonstrated that people would depend more or less on the prior belief of the trustees to assess their trustworthiness, either in one shot trust games or during repeated investment. A couple of fMRI studies have identified the brain structures that encode the value of various reputation priors (Delgado et al., 2005; Stanley et al., 2012; Fouragnan et al., 2013) or the learned reputation and its effect on the trust behavior (Singer et al., 2004; King-Casas et al., 2005; Wardle et al., 2013). Among them, one study has shown that the activities of the caudate of the trustors' brain differentiated between encountering good and bad trustees (Wardle et al., 2013). The authors put that this reflected the caudate's role of maintaining information of outcomes and facilitating good decision making, as suggested in the reinforcement learning model, in a social decision making domain. Comparatively, less attention has been paid to the ERP mechanisms of reputation learning. The only two ERP studies, as far as we know, that aimed to uncover the reputation learning process in games were conducted by Osinsky et al. (2014) and Bell et al.'s (2016). In the research of Osinsky et al. (2014), a repeated ultimatum game, in which subjects interacted with fair or unfair proposers, was adopted. Subjects saw the face of a proposer each time before the monetary offer was presented. It is reported that only in the later period of the repeated interactions, could subjects differentiate reputation of the proposers. Furthermore, this differentiation was indicated by the discrepancy in the amplitude of the frontocentral cue-elicited feedback negativity (FN) when subjects saw the faces of proposers. This study suggested that learned reputation would be ascribed to the social partners after repeated interactions with them and the identity (i.e., face) of a partner would become a predictive cue for the fairness of the offer that followed. Moreover, the FN induced by the faces of the partners could be an indicator of learned reputation. Bell et al.'s (2016), on the other hand, adopted a prisoner's dilemma game in their study and found an anterior positivity (400–600 ms) that was correlated with the retrieved reputation when a partner's face was shown after several rounds of interactions. This ERP component differed only between the faces with established reputation and the control faces, but not between cooperator and cheater faces.

Despite some effort in related research fields, the evolution of trustworthiness appraisal in iterated trust games and its ERP correlates remain unclear. In this study, we aimed to investigate the trustors' learning of their partners' reputation from multi-round interactions by observing both behavioral performance and neural activities of them throughout this learning process. We adopted an ERP experiment in which subjects acted as trustors in a repeated trust game and play with several trustees alternately. There were both "good" and "bad" trustees who would generally or seldom reciprocate respectively. Subjects were not provided with the information of their partners' trustworthiness throughout the game. Nonetheless, we predicted that subjects would get to know the trustees as their experience with each trustee accumulated. They would start with knowing little about their partners and end with recognizing the "good" and the "bad" to a large extent through learning. This interaction-based learning would be reflected in their investment decisions while the ascribed reputation to each trustee would finally be indexed by certain ERP components. Specifically, when the game was played repeatedly, subjects should become more likely to trust those partners who often reciprocated and avoid investing to those who were not. Besides, when the differentiation of trustworthiness evaluation was formed, it should also be reflected by the differentiation of the ERP time course related to trustworthiness appraisal.

Based on previous research, we were interested in several ERP components that may be involved in this study. First, we hypothesized that an anterior negative brain potential peaking ∼250 ms (Nieuwenhuis et al., 2004b; Donkers et al., 2005; Hajcak et al., 2006; San Martín, 2012) after the face stimuli could be a candidate component, the amplitude of which would differ after subjects had learned the trustees' reputation and their strategies had been guided by the trustworthiness evaluation. This ERP component, usually mentioned as the FN, has been shown to reflect a binary evaluation of outcomes (Nieuwenhuis et al., 2004a). A host of studies have demonstrated that the amplitude of this negativity is larger following negative compared to positive decision outcomes (Miltner et al., 1997; Gehring and Willoughby, 2002; Holroyd and Coles, 2002; Yeung and Sanfey, 2004; Sato et al., 2005; Hajcak et al., 2006; Santesso et al., 2012; von Borries et al., 2013; Meng and Ma, 2015). There are also studies suggesting that the association between the FN amplitude and feedback evaluation can be observed even in the absence of any executed actions before the feedback (Donkers et al., 2005; Yeung et al., 2005). Furthermore, some more recent studies (Walsh and Anderson, 2011; Osinsky et al., 2014) have extended the FN to an indicator of evaluation of the cue stimuli (coined as cue-elicited FN) when the valence of the outcome stimuli have transferred to the cues based on established rules or through evaluative learning. We supposed that when subjects had sufficiently formed differentiated evaluation of the two groups of trustees, the association between the faces of the trustees and the most probable monetary outcomes would be built. Thus, the valence of outcomes would transfer to the faces. As a result, subjects would form a rapid "good-vs-bad" evaluation seeing the faces when they have learned enough of the trustees' reputation, which would be indexed by the cue-elicited FN. Specifically, an increased negativity of the FN should be elicited by the faces of untrustworthy partners when reputation was well learned in the late period of the repeated interactions.

Second, we also surmised that once subjects formed the impression of their partners' trustworthiness in the late phase, the general emotional evaluation towards the faces should differ. Previous neuroscience research has posited that trustworthiness appraisals of faces involve an emotional face reaction in social settings (Winston et al., 2002; Singer et al., 2004; Engell et al., 2007; Yang et al., 2011; Stanley et al., 2012; Marzi et al., 2014). Thus, divergent neural responses toward the faces should also be reflected in magnitude differences of those late positive components including the P300 and LPP. These components were reported to be associated with emotional and motivational aspects of face processing (Langeslag et al., 2007; Grasso et al., 2009; Vico et al., 2010; Tortosa et al., 2013; Ma et al., 2015a) and have been found in previous studies of facial trustworthiness assessment (Yang et al., 2011; Marzi et al., 2014).

MATERIALS AND METHODS

Participants

Twenty-two male students from Zhejiang University participated in this experiment. Two of the subjects were excluded from the final analysis due to excessive electroencephalography (EEG) recording artifacts. The remaining 20 subjects (mean age = 22.75 years, standard deviation (SD) = 1.74) were all right-handed, had normal or corrected-to-normal vision. They reported no history of psychiatric or neurological disorders. All subjects provided written informed consent before the experiment. All procedures involving the subjects were in accordance with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. The study was approved by the Institutional Review Board of Neuromanagement Lab, Zhejiang University, Hangzhou, China.

Materials and Procedure

The basic experimental procedure required subjects to make a series of repeated investment decisions in a typical trust game setting. To better simulate the real-world situations where people usually have face-to-face interactions, we used eight male facial photographs to represent the trustees in the game (Chang et al., 2010). The photographs were selected from a dataset consisted of 24 young Chinese male facial photographs collected from the Internet. A calibration group of 177 males rated the attractiveness and the trustworthiness of these candidate faces on 7-point Likert scales (1 = extremely low on attractiveness/trustworthiness, 7 = extremely high on attractiveness/trustworthiness). The eight selected faces representing the trustees were close in both the attractiveness (mean = 2.889, *SE* = 0.177) and the trustworthiness (mean = 3.072, *SE* = 0.164) ratings. The photographs were all gray-scale, with the same clarity, luminance and size. The males on the photographs were full-face and in neutral facial expressions.

After arrival, subjects received a written instruction on the repeated trust game. They were told that in each round, they would decide whether to invest CNY ¥2 to the trustee; and if they did, the investment would quintuple and then the trustee might repay either CNY ¥5 or nothing. The basic paradigm is consistent with one of our own studies (Ma et al., 2015b). In the cover story, subjects were convinced that the eight trustees were students of Zhejiang University who had previously participated in similar trust games in our laboratory and we had collected their repayment decisions for this game. Therefore, subjects were informed of a nonreal-time interactive mode with real trustees but actually played against the computer. This manipulation adopted has been validated by several trust game experiments (Tzieropoulos et al., 2011; Tortosa et al., 2013; Wardle et al., 2013; Ma et al., 2015b). Among the eight pseudo-trustees, four were randomly assigned as trustworthy persons and would repay CNY ¥5 with a probability of 0.8 while the other four would "behave" untrustworthily, repaying CNY ¥5 only at a probability of 0.2 (Fouragnan et al., 2013). This assignment was reset when each subject started the task, so which four trustees were assigned to the trustworthy (untrustworthy) condition was different for each subject. Subjects were not explicitly told the number of the more or less trustworthy trustees or their repayment probabilities.

Subjects performed the experimental task comfortably seated 1 m away from the computer screen in an acoustically and electrically shielded room while their EEG was recorded. The task consisted of 240 trials, which were evenly divided into three blocks. These three blocks were designed to reflect a gradual process of learning, in which subjects could not have learned the trustees' reputation at the very beginning and could have successfully recognized the "good" from the "bad" by the end of the game. Therefore, we focused on the first and the last blocks and the trials in the second block were considered to be similar to the filler trials in previous studies of social neuroscience (Wu et al., 2012; Qu et al., 2013; Osinsky et al., 2014; Ma et al., 2015c). For instance, in a recent study, to compare the behavioral and neural responses before and after successful learning, only data from the first (early) and the last (late) blocks was analyzed (Alperin et al., 2014). Presentation of stimuli on a 17″ CRT monitor and subjects' keypad response recording were controlled by E-Prime software package (Psychology Software Tools, Pittsburgh, PA, USA). Each trial started with a fixation cross lasting for a random interval between 400 ms and 600 ms. After another random interval between 400 ms and 600 ms, the face of the trustee was presented for 1500 ms. Subjects would then see an endowment of CNY ¥2 and the two investment options ("invest" or "keep") on the screen after a random interval between 400 ms and 600 ms. They needed to press the "1" or "3" key once they had made the decision. The positions of the two options and their corresponding key buttons were counterbalanced across subjects. The chosen option would then be highlighted by a color change of its frame for 1000 ms. Following a random interval between 800 ms and 1000 ms, the repayment of the trustee would be shown for 1500 ms. The inter-trial random interval was between 700 ms and 900 ms. Experimental paradigm is illustrated in **Figure 1**.

Upon the completion of all trials, subjects would leave the room and rate each trustee's facial attractiveness and trustworthiness on a 7-point Likert scale (1 = "not attractive at all" or "not trustworthy at all", 7 = "highly attractive" or "highly trustworthy"). After the rating, they pressed the "Enter" key on another computer to draw an integer that would decide which one of the 240 trials would count. Subjects would get a bonus of CNY ¥0, ¥2 or ¥5 according to the actual investment and repayment of that trial besides their show-up fee of CNY ¥40. Finally, subjects were informed of the pseudo-trustee manipulation, thanked and paid out.

EEG Acquisition

During the task, EEG (band pass: 0.05–100 Hz; sampling rate: 1000 Hz) was recorded from 64 scalp sites according to the International 10–20 system with Ag/AgCl electrodes and a Neuroscan Synamp2 Amplifier (Scan 4.3.1, Neurosoft Labs Inc., Sterling, VA, USA). All electrodes were referenced to the left mastoid on-line and later off-line re-referenced to the linked mastoids. Vertical electrooculogram (EOG) was recorded with two electrodes placed above and beneath the left eye, while horizontal EOG was recorded with the other two placed at the outer canthus of each eye. The impedance was kept below 5 kΩ during recording.

Data Analysis

For the behavioral performance, the percentages of the "invest" choice in both the trustworthy and untrustworthy trustee conditions in each block were calculated as investment rates. The investment rates were then submitted to a

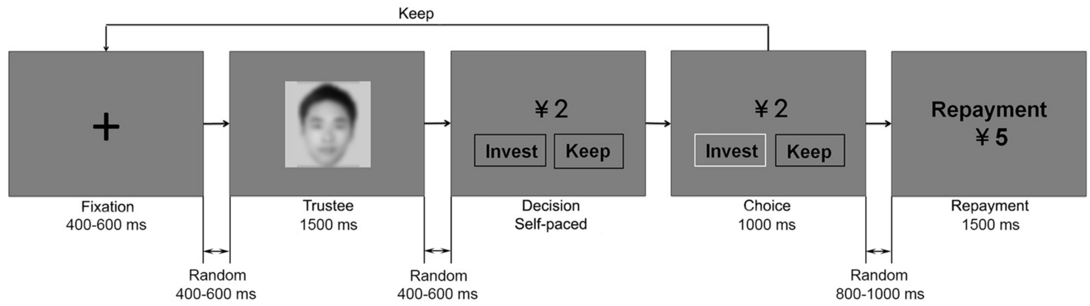

FIGURE 1 | Experiment procedure. In each trial, the face of the trustee was shown first. Subjects had to choose between "invest" and "keep". If they invested, the repayment of the trustee would then be revealed. If they kept the endowment, that round would end. In accordance with the research ethics of the journal, the face in this figure is obscured.

2 (trustworthiness: trustworthy, untrustworthy) × 2 (phase: early, late) repeated-measures analysis of variance (ANOVA). The response times of the investment choices were analyzed using the same 2 × 2 repeated-measures ANOVA. The Greenhouse-Geisser correction was applied for the violation of the sphericity assumption in ANOVAs (uncorrected degrees of freedom are reported with corrected *p*-values), and multiple comparisons were corrected with the Bonferroni method when appropriate. Furthermore, the averaged post-experimental attractiveness and trustworthiness ratings to the two types of trustees also went into paired *t*-tests.

In the ERP data off-line analysis, the vertical ocular artifact correction used the regression approach described by Semlitsch et al. (1986). Digital filtering was applied using a 30 Hz low pass filter (24 dB/octave). Data in the time window between 200 ms before and 800 ms after the face stimuli presentation was segmented and baseline-corrected by the pre-stimuli period. Trials with baseline-to-peak deflections that exceeded ±80 μV were then excluded from averaging. For each subject, the averaged ERPs were then created for each electrode under both trustworthy and untrustworthy conditions in both early and late phases.

Based on previous research and visual inspection on the grand averaged ERP waveforms and the scalp distribution, we conducted statistical analyses on three ERP components. For the FN component (mean amplitude: 200–260 ms), data from F3, Fz, F4, FC3, FCz and FC4 electrodes were analyzed. For both the P3 (mean amplitude: 300–420 ms) and LPP (mean amplitude: 420–720 ms) components, data from CP3, CPz, CP4, P3, Pz, P4, PO3, POz and PO4 were analyzed. Amplitudes of these ERP components were submitted to repeated-measures ANOVAs to test the effects of three factors: trustworthiness (trustworthy, untrustworthy), phase (early, late) and electrode. The Greenhouse-Geisser correction was applied for the violation of the sphericity assumption in ANOVAs (uncorrected degrees of freedom are reported with corrected *p*-values), and multiple comparisons were corrected with the Bonferroni method when appropriate.

RESULTS

Behavioral Results

Repeated-measures ANOVA showed that both trustworthiness ($F_{(1,19)} = 94.718, p < 0.001$) and phase ($F_{(1,19)} = 12.062, p = 0.003$) had significant effects on investment rate. Generally, subjects invested on trustworthy trustees (mean = 0.817, standard error (SE) = 0.029) more than untrustworthy ones (mean = 0.412, *SE* = 0.030) and their investment rate dropped through the early phase (mean = 0.659, *SE* = 0.024) to the late one (mean = 0.570, *SE* = 0.025). Furthermore, we found a significant interaction of trustworthiness and phase ($F_{(1,19)} = 71.145$, $p < 0.001$). Simple effect analysis firstly showed that investment rate was different in both phases. Subjects invested on trustworthy trustees (mean = 0.765, standard error (SE) = 0.030) more than untrustworthy ones (mean = 0.554, standard error (SE) = 0.034, $F_{(1,19)} = 24.917$, $p < 0.001$) in the early phase. In the late phase, the discrepancy in investment rate was more pronounced, with a rate of 0.869 (*SE* = 0.035) for trustworthy trustees and that of 0.271 (*SE* = 0.038) for untrustworthy ones ($F_{(1,19)} = 131.727$, $p < 0.001$). Furthermore, from the early to the late phase, investment rate for trustworthy trustees pronouncedly increased from 0.765 (*SE* = 0.030) to 0.869 (*SE* = 0.035; $F_{(1,19)} = 12.477$, $p = 0.002$) while this rate dramatically decreased from 0.554 (*SE* = 0.034) to 0.271 (*SE* = 0.038; $F_{(1,19)} = 52.845$, $p < 0.001$) for untrustworthy trustees.

The ANOVA on response time revealed no significant effect of trustworthiness ($F_{(1,19)} = 1.764$, $p = 0.200$) but a significant effect of phase ($F_{(1,19)} = 25.220$, $p < 0.001$). Subjects made faster decisions in the late phase (response time mean = 405.291 ms, *SE* = 40.157) than in the early phase (response time mean = 609.683 ms, *SE* = 53.115). No interaction of trustworthiness and phase was found ($F_{(1,19)} = 0.383$, $p = 0.543$).

Moreover, paired *t*-tests on the post-experimental ratings of the trustees' trustworthiness and attractiveness showed that trustees in the assigned trustworthy group were perceived to be not only more trustworthy (trustworthy: trustworthiness mean = 5.438, *SE* = 0.204; untrustworthy: trustworthiness

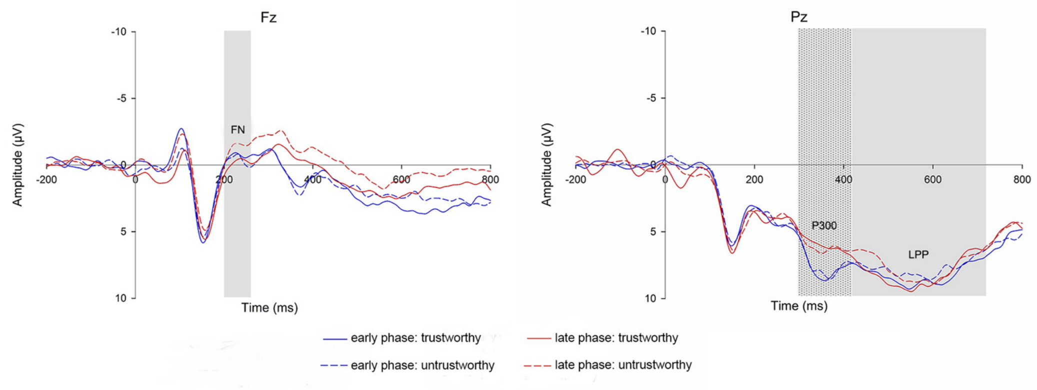

FIGURE 2 | Grand averaged event-related potentials (ERPs) at Fz (feedback negativity, FN) and Pz (P300 and LPP) comparing the four conditions over trustworthiness (trustworthy vs. untrustworthy) and phase (early vs. late). Rectangular shadows indicate the time windows of each component.

mean = 2.275, SE = 0.170; $t_{(19)} = 11.392$, $p < 0.001$) but also more attractive (trustworthy: attractiveness mean = 4.133, SE = 0.195; untrustworthy: attractiveness mean = 3.063, SE = 0.250; $t_{(19)} = 4.477$, $p < 0.001$) than those in the untrustworthy group.

ERP Results

The ERPs in the 2 (trustworthiness: trustworthy, untrustworthy) × 2 (phase: early, late) conditions are illustrated in **Figure 2**. Scalp topographies of the FN are shown in **Figure 3**.

FN

The ANOVA on the FN amplitude showed that neither the main effect of trustworthiness ($F_{(1,19)} = 2.619$, $p = 0.122$) nor that of phase ($F_{(1,19)} = 0.173$, $p = 0.682$) was significant, while a significant main effect of electrode was observed ($F_{(5,95)} = 5.517$, $p = 0.004$). FN amplitude reached negative maximum at Fz (mean = −0.620, SE = 0.701).

A significant interaction effect of trustworthiness and phase was manifested ($F_{(1,19)} = 5.089$, $p = 0.036$). An additional simple effect analysis revealed that in the early phase the FN amplitude difference was not significant in the two trustworthiness conditions (trustworthy: mean = 0.047, SE = 0.784; untrustworthy: mean = 0.076, SE = 0.721; $F_{(1,19)} = 0.004$, $p = 0.948$), but in the late phase the FN amplitude was significantly different in the two conditions (trustworthy: mean = 0.309, SE = 0.669; untrustworthy: mean = −0.703, SE = 0.761; $F_{(1,19)} = 9.688$, $p = 0.006$).

A significant interaction of trustworthiness and electrode was also found (trustworthiness × electrode: $F_{(5,95)} = 3.474$, $p = 0.018$). However, no other interaction effects were identified (phase × electrode: $F_{(5,95)} = 0.393$, $p = 0.756$; trustworthiness × phase × electrode: $F_{(5,95)} = 0.904$, $p = 0.449$).

P3 and LPP

The ANOVA on the P3 amplitude only revealed a significant effect of electrode ($F_{(8,152)} = 12.856$, $p < 0.001$), such that the P3 amplitude was largest at PO3 (mean = 9.171, SE = 1.055). However, no other effects were found (trustworthiness: $F_{(1,19)} = 1.415$, $p = 0.249$; phase: $F_{(1,19)} = 2.789$, $p = 0.111$; trustworthiness × phase: $F_{(1,19)} = 0.844$, $p = 0.370$; trustworthiness × electrode: $F_{(8,152)} = 1.034$, $p = 0.385$; phase × electrode: $F_{(8,152)} = 1.539$, $p = 0.215$; trustworthiness × phase × electrode: $F_{(8,152)} = 0.539$, $p = 0.709$).

Similarly, the ANOVA on the LPP amplitude found that none of the effects were significant (trustworthiness: $F_{(1,19)} = 1.804 = 0.195$; phase: $F_{(1,19)} =$, $p = 0.931$; electrode: $F_{(8,152)} = 3.131$, $p = 0.057$; trustworthiness × phase: $F_{(1,19)} = 0.035$, $p = 0.854$; trustworthiness × electrode: $F_{(8,152)} = 1.261$, $p = 0.291$; phase × electrode: $F_{(8,152)} = 1.071$, $p = 0.364$; trustworthiness × phase × electrode: $F_{(8,152)} = 0.444$, $p = 0.796$).

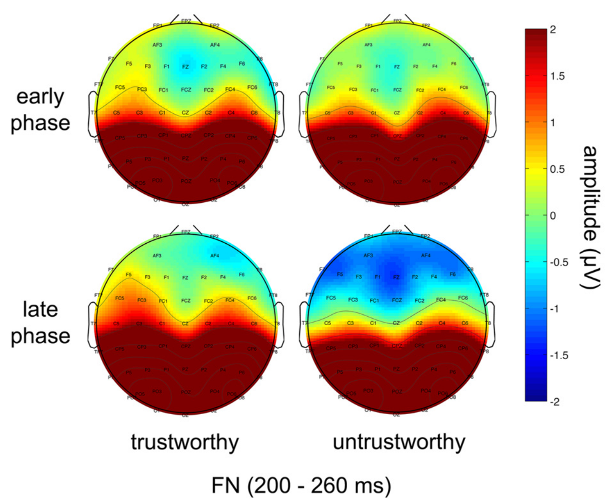

FIGURE 3 | Topographical maps showing scalp distributions of the FN amplitudes in the trustworthy (left) and the untrustworthy (right) conditions in the early (upper) and the late (lower) phases.

DISCUSSION

In the present study, we explored the learning process of evaluating others' trustworthiness during repeated social interactions. In social interaction circumstances, trust is defined as the trustor's willingness to accept vulnerability based on positive expectations of the actions of the trustee (Rousseau et al., 1998). Trustworthiness, then, is the reciprocity of the trustee that honors trust (Ashraf et al., 2006). Our study clearly shows that the partners' trustworthiness strongly influences the trustors' propensity to trust. The experiment data has proved that, overall, subjects invested more to those who often reciprocated. More importantly, subjects were getting better at evaluating their partners' reputation as the interactions proceeded. Hence, they became more willing to invest in the trustworthy partners and drastically shrank from those who seldom repaid. It is worth noting that, although the investment rate has been different in the early phase, suggesting that there has already been some opportunity for reputation learning at that time, the discrepancy of investment rate significantly magnified in the late phase. This strategy adjustment reveals that they were learning to discriminate "good" trustees from "bad" ones throughout the game. Besides investment rate, the decreasing response time also suggests that subjects got more confident as they could gradually differentiate between two kinds of partners. Additionally, the result of the post-experimental trustworthiness rating is again a piece of evidence for this differentiation.

Subjects' largely successful learning of their partners' trustworthiness has been reflected by the electrophysiological dynamics during this repeated trust game. Our ERP results suggest that amplitude of the cue-elicited FN is associated with the differentiation of trustworthiness. In the early phase when subjects were not that clear about their partners' characteristics, the FN amplitude was not significantly different when they saw the faces of the partners. In the late phase, however, a significant discrepancy of the FN amplitude was manifested, corresponding with the well-established investment discrimination between the two groups of partners. Hence, this component is proved to be a neural correlate of trustworthiness assessment in our experiment. The cue-elicited FN was more negative in the untrustworthy than the trustworthy trustee condition as hypothesized. This result is in line with the previous consensus that the FN, which maximizes at the medial frontal sites (Yeung et al., 2005; von Borries et al., 2013), is larger when an unfavorable stimulus is presented (Miltner et al., 1997; Gehring and Willoughby, 2002; Holroyd and Coles, 2002; Nieuwenhuis et al., 2004b; Yeung and Sanfey, 2004; Donkers et al., 2005; Sato et al., 2005; Yeung et al., 2005; Hajcak et al., 2006; Santesso et al., 2012; von Borries et al., 2013; Ma et al., 2015b).

Early research has shown that emotional contexts associated with faces could modulate very early (30–60 ms) sensory processing in visual areas and amygdala, which was reflected in magneto-encephalographic responses (Morel et al., 2012). In our experiment, the differentiation of the cue-elicited FN under different trustworthiness conditions in the late phase exhibits that trustworthiness appraisal can also be an immediate response when reputation was formed to a large extent, which is consistent with findings of existing behavior and ERP studies (Willis and Todorov, 2006; Todorov et al., 2009; Marzi et al., 2014). In these studies, evaluation on trustworthiness basing only on facial characteristics could be done within 100 ms and was reflected by early ERP components. Our result further shows that judgment of trustworthiness based on previous experience in social interactions can be formed in barely more than 200 ms, even when an explicit requirement of judging or decision making is absent. We again suggest that trustworthiness assessment should be a fast process that facilitates human social decision making.

Furthermore, trustworthiness appraisal embedded in the cue-elicited FN component evolved along with the learning of reputation when no prior information was provided. In our experiment, since each investment basically had a positive expected value (i.e., ¥0.5) when no information of the trustee's reputation was available (i.e., the probability of getting repayment was equal to that of getting nothing), subjects were inclined to invest in each round at the very beginning. As the interactions advanced, they gradually recognized each partner's reputation and adjusted their strategy. Therefore, when subjects saw the face of a trustee, they became more and more able to evaluate whether this man was likely to reciprocate their trust and whether they should invest in him. Unlike Bell et al.'s (2016) research where subjects also learned their partners' reputation but the late anterior positivity only encoded whether there was retrieved socially salient memory (i.e., learned reputation) of a face, our study has shown an early ERP component that differed between two types of partners. When the reputation was sufficiently created, the faces of the trustees would become stimuli that afforded the "good-vs-bad" valence disparity derived from a learned association with the general investment outcomes of the trustees. As an electrophysiological indicator of the binary evaluation of the faces, the FN differed in amplitude in the late phase. Our results corroborate the reinforcement learning theory of the FN (Holroyd and Coles, 2002; Nieuwenhuis et al., 2004a; Hajcak et al., 2007) and existing studies that have found the valence-based amplitude disparity of the cue-elicited FN (Dunning and Hajcak, 2007; Baker and Holroyd, 2009; Liao et al., 2011; Walsh and Anderson, 2011). The modulation on cue-elicited FN amplitude by the learned reputation in the late phase is also consistent with the results found by the previously mentioned ERP study of reputation learning during a repeated ultimatum game (Osinsky et al., 2014). However, unlike the certain or probabilistic simple cues that predicted the favorableness of following outcomes based on fixed rules or the social cues that were completely indicative of the upcoming payoff after learning in social interactions, the faces in our experiment were less predictive but more instructive to what should happen next. Therefore, the face-induced FN in this study reflected not only the reputation assessment but also an instruction to the later investment decision. Our study complements findings of Osinsky et al. (2014) by providing similar neural evidence in a different repeated trust game, which also suggests that the cue-elicited FN may be a neural index of reputation learning in repeated social interactions.

Besides, our ERP results are in line with previous fMRI research regarding reputation learning in trust games (Wardle et al., 2013), suggesting that when the identities of the trustees act as cues, they maintain information that guides decision making and supporting a reinforcement learning model during the trustors' learning process.

In the late components, however, we did not find any differentiation corresponding with the learning process through the early to the late phase of the game. The posterior P300 and LPP amplitudes did not differ in the two trustworthiness conditions when subjects had already learned most of their partners' reputation, which is contrary to the results of some studies regarding trustworthiness appraisals of faces (Yang et al., 2011; Marzi et al., 2014). One possible reason for this inconsistency is the difference in experiment design of our study and the others. Our experiment did not ask subjects to explicitly rate the trustworthiness of the trustees. Besides, subjects' implicit evaluation on the trustworthiness of the trustees was based on social experience. In the studies of Yang et al. (2011) and Marzi et al. (2014), participants resorted to those common physical characteristics to infer trustworthiness instead. Actually, in a previous research regarding face evaluation, similar findings suggesting that the direction of the relationship between stimuli valence and amplitudes of the late positive components was inconsistent were also reported. The authors suggested that this seemingly contradictory finding might be the result of the discrepancy in experimental paradigm (Chen et al., 2012). On the other hand, based on the assumption that trustworthiness appraisal is a generalization of emotion evaluation, the studies on facial trustworthiness and the late components attributed the difference of P300 or LPP to the motivational difference of emotion induced by different faces. However, fMRI studies regarding the relationship between amygdala activation and trustworthiness evaluation, which also posited that the amygdala processed the emotional stimuli, have demonstrated inconsistent results on the direction of this relationship (Adolphs et al., 1998; Winston et al., 2002; Singer et al., 2004; Engell et al., 2007; Todorov et al., 2008; Mattavelli et al., 2012; Freeman et al., 2014). In addition, a relatively small sample size may not fully reveal a potential learned trustworthiness effect on P300/LPP in our study. Therefore, the neural response underlying the emotional processing of learned facial trustworthiness needs further investigation in future research, especially that with large sample sizes, which is beyond the scope of the present study.

Interestingly, we have found that the post-experimental facial attractiveness rating was significantly different between the two trustworthiness conditions. Subjects rated faces of those more trustworthy trustees as more attractive. We think that this discrepancy of rating cannot be accounted by facial attractiveness differences of the face stimuli. First, before the experiment, the faces were similarly rated in attractiveness by the calibration group. Second, each face was randomly reassigned to one of the trustworthiness conditions so that the same face was not always placed in the same condition. These manipulations should have excluded facial attractiveness from the factors that influenced the behavioral or ERP results (see Chen et al., 2012). We assume that our result manifests "what is good is beautiful", which has been suggested by existing research on facial attractiveness judgment showing that positive personality traits could enhance a person's facial attractiveness rated by others (Zhang et al., 2014). Besides, a neuroscientific study has revealed that activation of some brain regions increase/decrease as a function of both attractiveness and goodness, providing some implications for understanding why judgments of these two dimensions are usually highly correlated (Tsukiura and Cabeza, 2011). Our study, however, involved a learned trustworthiness evaluation and showed its contribution to facial attractiveness rating. Thus, it implies that repeated interactions can not only form our judgment to others' social reputation but also influence our perception of their physical features.

CONCLUSION

The present study investigated a process in which the trustors learned the trustees' trustworthiness by observing their behavior and adjusted their own trust decisions accordingly. The ERP results revealed that magnitudes of the cue-elicited FN varied as whether the trustors saw the trustworthy or untrustworthy trustees, but only in the later period of the repeated trust game. Therefore, we suggest the cue-elicited FN as an early ERP index of reputation appraisal in repeated social exchanges, which corroborates and complements previous findings (Osinsky et al., 2014). In summary, our study demonstrates that one's implicit rating of social partners' trustworthiness that is gradually formed through interactions with them will affect her/his trust behavior and the gradual differentiation of the cue-elicited FN component reflects this learning process.

AUTHOR CONTRIBUTIONS

DL and LM conceived the study and designed the experiment. DL ran the experiment, analyzed the data and drafted the manuscript. DL, LM and QM revisited the manuscript.

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Corrigendum: Who Deserves My Trust? Cue-Elicited Feedback Negativity Tracks Reputation Learning in Repeated Social Interactions

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Neural Correlates of Consumer Buying Motivations: A 7T functional Magnetic Resonance Imaging (fMRI) Study

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Consumer buying motivations can be distinguished into three categories: functional, experiential, or symbolic motivations (Keller, 1993). Although prior neuroimaging studies have examined the neural substrates which enable these motivations, direct comparisons between these three types of consumer motivations have yet to be made. In the current study, we used 7 Tesla (7T) functional magnetic resonance imaging (fMRI) to assess the neural correlates of each motivation by instructing participants to view common consumer goods while emphasizing either functional, experiential, or symbolic values of these products. The results demonstrated mostly consistent activations between symbolic and experiential motivations. Although, these motivations differed in that symbolic motivation was associated with medial frontal gyrus (MFG) activation, whereas experiential motivation was associated with posterior cingulate cortex (PCC) activation. Functional motivation was associated with dorsolateral prefrontal cortex (DLPFC) activation, as compared to other motivations. These findings provide a neural basis for how symbolic and experiential motivations may be similar, yet different in subtle ways. Furthermore, the dissociation of functional motivation within the DLPFC supports the notion that this motivation relies on executive function processes relatively more than hedonic motivation. These findings provide a better understanding of the underlying neural functioning which may contribute to poor self-control choices.

Keywords: consumer, motivation, decision, fmri, prefrontal cortex

INTRODUCTION

Motivation can be broadly defined as an internal impetus to act and carry out behaviors which can vary in both intensity and type of valuation (Ryan and Deci, 2000). The predominant model of consumer buying motivations has identified functional, experiential, and symbolic types of values as fundamental needs (Keller, 1993). According to this theoretical understanding of consumer motivations, information processing contributing to a purchase decision differs for each motivation. When individuals are motivated by functional needs, their decision making is primarily determined by instrumental benefits (e.g., financial savings, quality, or security); whereas when their motivation is experiential, their decision is determined by emotional or hedonic benefits such as the fun and excitement the product can provide (Dhar and Wertenbroch, 2000). An individual's purchase decision can also be motivated by symbolic needs based on social cognition where they seek products that provide social benefits such as conveying their taste and status or enhancing their self-image in a social setting (Keller, 1993; Verplanken and Sato, 2011). Prioritization of self-directed functional, experiential, and symbolic valuation of products is a reliable predictor of purchasing behavior (Kim et al., 2002). Dissociations of functional, experiential, and symbolic motivations have been well-documented in behavioral studies and shown to influence purchasing behavior. However, new knowledge about the neural bases of functional, experiential, and symbolic valuations will provide increased understanding of the mechanisms involved in consumer decisions and differences in information processing between consumer motivations.

Among the approaches to understanding the distributed neural functioning which enables motivational values, consumer choice methods are ideal. As an increasingly popular topic in neuroimaging literature, consumer choice-making studies have extended the understanding of how people interact and behave in a contemporary environment (Lee et al., 2007). Thus, the implications of these studies expand well beyond commercial aims and relate broadly to examinations of consumer choice and decision-making. One traditional area of consumer research with limited utilization of neuroimaging methods has been investigations of motivational states on consumer choices. Although support for the internal validity of the functional, experiential, and symbolic motivations has been demonstrated behaviorally, to date, limited studies have directly examined these consumer buying motivations using functional neuroimaging to validate the proposed differences in information processing across various motivations (Erk et al., 2002; McClure et al., 2004; Tsai et al., 2006; Levy et al., 2011).

Erk et al. (2002) examined functional and symbolic consumer motivations using fMRI during an image rating task. They found that artificial cultural objects (i.e., luxury and sport cars) associated with wealth and social dominance elicit activation in reward-related brain areas (i.e., right ventral striatum, left anterior cingulate and bilateral prefrontal cortex). Alternatively, practical and economical objects (i.e., small cars) were associated with deactivations among these regions (Erk et al., 2002). In a similar study of functional and symbolic motivations, Schaefer and Rotte (2007) assessed the neural basis for different categories of culturally based brands affecting people's purchasing decisions. The findings revealed that the medial prefrontal cortex (MPFC) and precuneus demonstrated greater activation when comparing symbolic motivation (i.e., sports and luxury car brands) to functional motivation (i.e., unfamiliar product labels or value brands). This finding led the authors to assert that the perception of brands that are related to high or low social dominance modulated purchasing decisions via greater activations in the MPFC and precuneus.

Prior neuroimaging findings involving comparisons of functional and symbolic motivations are largely consistent with the theoretical understanding of these valuations. The MPFC has been related to self-reflection and self-relevant processing (Johnson et al., 2002; Ochsner et al., 2004). Additionally, both the anterior medial cortex (medial frontal gyrus and anterior cingulate cortex) and posterior medial cortex (PCC and/or precuneus) have been implicated in self-referential processing (Ochsner et al., 2004; Vogt and Laureys, 2005). Johnson et al. (2006) dissociated MPFC and PCC activity during self-reflection, positing that the MPFC is associated with instrumental or agentic self-reflection, whereas the PCC is associated with experiential self-reflection. Medial areas of the prefrontal cortex (PFC) have traditionally been implicated in affective/motivational systems, whereas lateral areas tend to be more involved in sensory/motor processing. Accordingly, O'Reilly's (2010) model has proposed a functional division within the cognitive control network of the PFC in which the lateral PFC underlies goal-oriented behavior guided by non-arousing, neutral information (*cold processing)*, whereas the medial PFC underlies goal-oriented behavior guided by arousing and pleasant information (*hot processing*).

One limitation of prior neuroimaging studies of consumer motivations involves comparing only functional and symbolic valuations. Keller (1993) identifies fundamental values as functional, experiential, and symbolic. Thus, it remains unclear whether self-referential neural activity is associated with both symbolic and experiential, but not with functional motivations. Furthermore, self-referential valuations may be associated with inward or outward reflection (Johnson et al., 2006). Accordingly, investigations to dissociate the neural circuitry between experiential and symbolic motivations, and how these uniquely differ from functional motivations have remained elusive. By comparing each of Keller's (1993) three motivations using an instructed valuation task, we hypothesized that dissociations within the lateral to medial PFC would emerge with respect to functional, experiential, and symbolic types of consumer motivations.

The current study aimed to test this hypothesis in the context of a consumer decision task during blood-oxygen-level-dependent (BOLD) fMRI data acquisitions. Based on the prior literature discussed above, it was hypothesized that task-related activations during the functional condition should be associated with greater activity in cognitive-control related regions previously implicated in studies involving a response to instrumental benefits, in particular, the dorsolateral prefrontal cortex (DLPFC). Task-related activations during the experiential condition should lead to greater activity in regions including the PCC associated with inward-directed self-reflection, such as self-emotional or self-hedonic benefit. Task-related activations during the symbolic condition should lead to greater activity in regions including the MPFC implicated in the outward-directed self-reflection process, such as social benefits.

METHODS

Participants

Participants were recruited following an initial interview in which volunteers self-reported being right-handed and having normal or corrected-to-normal vision. All participants provided written informed consent prior to any training or image acquisition and were financially compensated for their time. Ten volunteers (age range = 19–24 years; five females) served as experimental subjects. A power analysis technique (Mumford and Nichols, 2008) was used to decide the sample size. Accordingly, we based the effect sizes on a subset of participants ($n = 5$) and our regions of interests (MPFC, PCC and DLPFC, defined from Automated Anatomical Labeling atlas). The power curve revealed that 10 subjects were sufficient to achieve 75% calculation power for group fMRI experiments (See Supplementary Figure 1). All experimental methods and procedures were approved by the Auburn University Institutional Review Board.

Stimuli

Eighteen generic products were selected based on the results from a series of pilot studies administered to Auburn University undergraduates. Through the first pilot survey ($n = 135$), a pool of 152 products appealing to college-aged consumers were identified, among which 34 products were then selected to be gender-neutral and non-seasonal by a panel of experts ($n = 7$) consisting of three and two faculty members from consumer sciences and psychology, respectively, and two graduate students from consumer sciences. The second pilot survey ($n = 102$) established 18 among the 34 products to represent varying levels of expensiveness (ranging from "not expensive at all" to "very expensive") and buying and promotion frequencies (ranging from "once every few years" to "always") to college students. Four of these generic products (i.e., car, pasta sauce, sunglasses, and tablet computer) were selected to serve as training stimuli, which were used in practice versions of the task (to be performed outside the scanner) designed to be similar to the actual task. The remaining 14 products (bikes, blu-ray players, books, cellphones, cellphone cases, drinks, DVDs, laptop computers, mugs, plane tickets, shower curtains, towels, TVs, and workout apparel) were presented in pictorial stimuli which visually and verbally depicted these consumer goods in scenarios representing either a functional, experiential, or symbolic motivational condition.

For each product, three scenarios were created per motivational condition so that they contained varying visual and verbal descriptions of the same motivational condition. Therefore, nine stimuli were generated by nesting the three motivational conditions and the three visual/verbal scenarios for each of the 14 generic consumer goods (see **Figure 1**), resulting in a total of 126 buying scenarios. The 126 scenarios were subjected to a behavioral pretest with a sample of 274 Auburn University undergraduates. To prevent disturbance effects from subjects' fatigue, each pretest subject evaluated only a partial set among the 126 scenarios assigned to them according to a mixed design. First, the 14 products were grouped into two sets of seven products. The subjects were randomly assigned to one of the two product sets. Then, they were shown all nine motivational condition scenarios of each assigned product. Each scenario was rated on one of the following three motivational likelihood questions, randomly assigned: "If you shop for [product name] for the above occasion, how likely are you to consider" (1) "its functional and practical aspects" (i.e., functional value), (2) "the fun and excitement it can offer" (i.e., experiential value), or (3) "whether it can tell something about yourself" (i.e., symbolic value). The questions were answered using a 5-point Likert scale (1 = very unlikely, 5 = very likely), and the scenario presentation order was counterbalanced across subjects. This mixed design led to six stimulus blocks (see **Table 1**), each of which was individually analyzed employing repeated measures ANOVA for a three-way Product (7) $\times$ Motivation Scenario (3) $\times$ Motivational Likelihood Question (3) design. Motivational Likelihood Question was a between-subjects factor, whereas Product and Motivation Scenario were within-subjects factors. The results revealed significant ($p < 0.001$) Motivation Scenario $\times$ Motivational Likelihood Question interaction effects for all six stimulus blocks, confirming that the subjects were most likely to consider the respective product values that matched the motivational scenarios of the stimuli (see **Table 1**).

Task Design

Each of the 126 buying scenario stimuli comprised a single trial of the task. **Figure 2** depicts a typical trial progression (mean 13-s duration) which always began with the onset of a stimulus presentation (8-s duration), followed by a question prompt (5-s duration) and then progressed to a variable inter-trial interval (ITI; mean = 8-s) which contained a central fixation cross. The variable ITI served to jitter the onset of stimuli and conditions with TRs to better estimate the hemodynamic response function (HRF) which underlies motivational conditions. During the question prompt, participants indicated what they considered most important if they were to buy the product for the particular situation using three buttons from a standard, 4-button, MR-compatible button box (Current Designs, Philadelphia, PA). They pressed 1 for "the functional and practical value of the product" (functional motivation), 2 for "the pleasantness, joy, or excitement the product can offer" (experiential motivation), or 3 for "your status, lifestyle, or taste that the product shows" (symbolic motivation).

The task was divided into three blocks of 42 trials each. Optseq (http://surfer.nmr.mgh.harvard.edu/optseq/) was used to determine an ideal sequence of variable ITIs and trials corresponding to motivational conditions which maximized the variance of the predicted fMRI response and thereby minimized the overlap of HRFs during blocks of event-related fMRI designs. The inputs for Optseq were specified for the finite impulse response (FIN) window with no (0-s) minimum, a 10-s maximum, a minimum 1-s post-stimulus delay. Additionally, a variable ITI would last between 4-s and 10-s. The motivational conditions depicted by the visual/verbal scenarios were counterbalanced within each run to be presented an equal number of times.

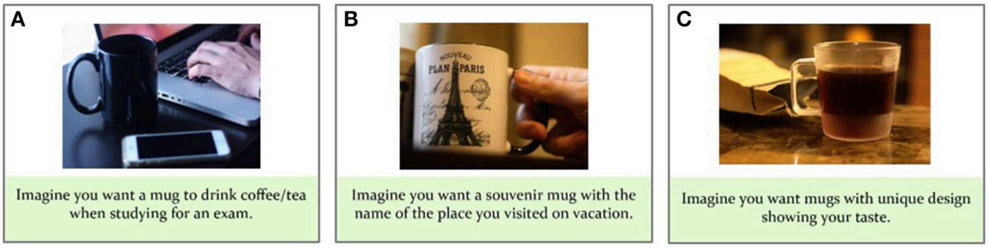

FIGURE 1 | Example stimuli. Examples of three motivational categories for products (e.g., mugs) depicted in pictorial stimuli with instructed buying motivations for the product. **(A)** Functional, **(B)** experiential, and **(C)** symbolic motivation. Note that none of the example images are part of the experimental stimulus material used in the current study. The copyright lies with the authors, and no permission was required for the reproduction of these images.

TABLE 1 | Results from the behavioral pretest of the stimuli.

Stimulus block[a]	Motivation scenario	Likelihood to consider[b]			$F(df1, df2)$[c]	p
		Functional value	Experiential value	Symbolic value		
1	Functional	4.58	3.09	3.32	77.34 (4, 266)	<0.001
	Experiential	3.44	4.09	3.63		
	Symbolic	3.40	3.75	4.05		
2	Functional	4.21	2.61	2.97	71.52 (4, 266)	<0.001
	Experiential	3.63	3.98	3.71		
	Symbolic	3.47	3.52	4.04		
3	Functional	4.46	2.54	2.48	102.47 (4, 266)	<0.001
	Experiential	3.46	3.91	3.61		
	Symbolic	3.05	3.60	4.19		
4	Functional	4.30	2.57	2.47	73.23 (4, 270)	<0.001
	Experiential	3.43	4.07	3.39		
	Symbolic	3.23	3.60	3.70		
5	Functional	4.25	2.97	2.88	71.31 (4, 270)	<0.001
	Experiential	3.30	4.01	3.26		
	Symbolic	3.08	3.46	3.85		
6	Functional	4.25	2.67	2.61	90.35 (4, 270)	<0.001
	Experiential	3.24	4.18	3.33		
	Symbolic	2.87	3.26	3.88		

[a] *Stimulus blocks 1 through 3 used seven products (laptop computers, mugs, plane tickets, shower curtains, towels, cell phones, and workout apparel), whereas stimulus blocks 4 through 6 used the remaining seven products. Each stimulus block contained only one of the three scenarios tested for each of its respective product × motivation cells.*
[b] *The reported numbers are means.*
[c] *The test statistics reported are for the two-way Motivation Scenario (3) × Motivational Likelihood Question (3) interaction.*

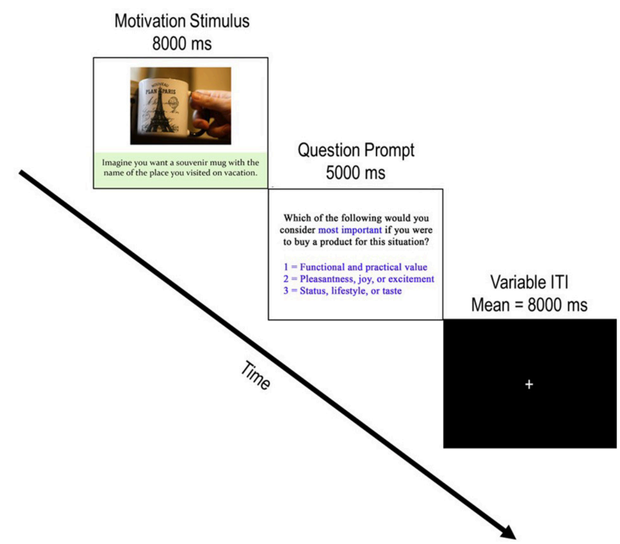

FIGURE 2 | Depiction of a typical trial progression. Each trial begins with the presentation of a product stimulus accompanied by a buying motivation scenario. After the motivation stimulus was presented for 8,000 ms, the question prompt screen appeared for 5,000 ms and incited participants to report which buying motivation they considered by pressing 1 of the three possible responses. Following the question prompt, a jittered ITI with a central fixation appeared. Participants were instructed to focus on the fixation cross and awaited the next trial during these periods. Note that the example image is not part of the experimental stimulus material used in the current study. The copyright lies with the authors, and no permission was required for the reproduction of this image.

Experimental Procedure

To ensure comprehension of the task requirements, all participants completed a practice version of the task prior to scanning using a standard PC, LCD monitor, and keyboard. The practice task was identical to the task implemented during scanning; however, only cars, pasta sauce, sunglasses, and tablet computers were presented with visual/verbal scenarios emphasizing either the functional, experiential, or symbolic values of each product. Following this practice version of the task, participants completed an additional practice version of the task using the same four practice stimulus items once inside the scanner, during a echo-planar imaging (EPI) BOLD acquisition sequence similar to the actual task scan. This additional practice task was conducted during MR scanning to ensure that participants were acclimated to the MR-compatible button box and rear-mounted projector screen, as well as the scanning environment during conditions identical to the actual imaging acquisition sequence. All experimental events during the practice task and actual task completed during scanning were presented using a standard PC, and MR-compatible rear-mounted projector screen and projector (Silent Vision, http://www.avotecinc.com/). Events were controlled and recorded using a custom program written with E-prime 2 software (http://www.pstnet.com/). However, only data from the actual tasks were analyzed and those from the practice task (both inside and outside the scanner) were not submitted to further analysis.

Data Collection

This study was carried out on a 7 Tesla (T) MAGNETOM scanner (Siemens Healthcare, Erlangen, Germany) using 32-channel head coil at the Auburn University MRI Research Center in Auburn, AL, USA. Prior studies have shown higher functional specificity using 7T vs. 3T in terms of percent signal change, mean t-values, number of supra-threshold voxels, and contrast to noise ratio (Beisteiner et al., 2011; Geißler et al., 2014). Thus, compared to using the same number of subjects at 3T, the likelihood of detecting true activations is better at 7T. Functional brain imaging data were acquired using a multiband echo-planar imaging sequence (Feinberg et al., 2010) with repetition time (TR) = 1-s, echo time (TE) = 20-ms, slice thickness = 2 mm, gap between slices =3 mm, flip angle =70°, in-plane resolution of 2 × 2 mm^2, and multi-band factor of 2. Also, a high-resolution 3D MPRAGE sequence was used to collect T1-weighted structural data for anatomical localization for the fMRI data. Visual stimuli were presented to participants in three different runs per session, with each run lasting approximately 16 min. Runs were randomized for each participant, but were counterbalanced to consist of 42 trials with 14 trials for each of the three motivations, selected without replacement.

fMRI Data Analysis

Preprocessing

All data preparation and preprocessing steps, as well as statistical analysis, were conducted with Statistical Parametric Mapping (http://www.fil.ion.ucl.ac.uk/spm/software/spm8/) under MATLAB environment. Standard image preprocessing was performed including realignment (motion correction), normalization, smoothing, and detrending. Motion correction was performed, to detect and correct for head movements, by spatial alignment of all volumes to the first volume by rigid body transformations. Translation and rotation parameters were inspected and never exceeded 1 mm or 1°, respectively. Then, we normalized MRI images into Montreal Neurological Institute (MNI) standard brain template space using nonlinear warping. All functional imaging data were spatially smoothed with 6 mm FWHM Gaussian kernel.

Statistical Analysis

After preprocessing the raw data, BOLD fMRI data were analyzed in normalized space using a General Linear Model implemented in SPM8. The time course of brain activation was modeled with a boxcar function convolved with the canonical hemodynamic response function (HRF), including the time and dispersion derivative function allowing for variations in subject-subject level and voxel-voxel response. After obtaining the estimated β, voxel level inter-subjects and between-subjects linear contrasts were computed using different t-tests methods. The statistical threshold of significance was set at $p < 0.05$ (FDR corrected). Functional maps were overlaid on the MNI T1-weighted brain template.

In order to assess the neurofunctional correlates which underlie each of the three motivations for consumer decisions, task-related activations specific to the 8-s motivation stimulus presentation (see **Figure 2**) were compared between stimulus presentation durations for each trial type. Given the emotion-relevant information associated with experiential and symbolic motivations of consumer decisions, these motivation conditions should reflect relatively hot processing as compared to the relative cold processing in functional conditions. Accordingly, separate contrasts comparing functional and experiential motivation trials, and functional and symbolic trials were assessed. Because there was an expectation for considerable overlap between experiential and symbolic conditions, it was necessary to assess activations unique to experiential and symbolic motivations. A third contrast compared functional trials to both experiential and symbolic trials. Likewise, a fourth contrast compared experiential trials to both symbolic and functional trials. A final contrast assessed activations unique to symbolic motivation by comparing functional trials to both functional and experiential trials. All contrasts were computed using unpaired (pooling) t-tests. All comparisons were run as two-tailed tests; however, only contrasts that yielded significant differences in activation passing the FDR corrected threshold are reported.

RESULTS

fMRI Results

I. Experiential Motivation > Functional Motivation for Display

Figure 3 shows the results of t-tests for the contrast that compared experiential motivation to functional motivation for display condition. The results of this comparison yielded activations in the MFG, precuneus, PCC, caudate, putamen, parahippocampal cortex (PHC) and amygdala cluster, and inferior frontal gyrus (IFG).

II. Symbolic Motivation > Functional Motivation for Display

Figure 4 shows the results of t-tests for the contrast that compared symbolic motivation to functional motivation during stimulus display periods. The results of this comparison yielded activations in the MFG, precuneus, and PCC.

III. Functional Motivation > Symbolic and Experiential Motivations for Display

Figure 5 shows the results of t-tests for the contrast that compared the functional motivation to the experiential and symbolic motivations. Activation only in the DLPFC was significant.

IV. Experiential Motivation > Functional and Symbolic Motivation for Display

Figure 6 shows the results of t-tests for the contrast that compared experiential motivation scenarios to the functional

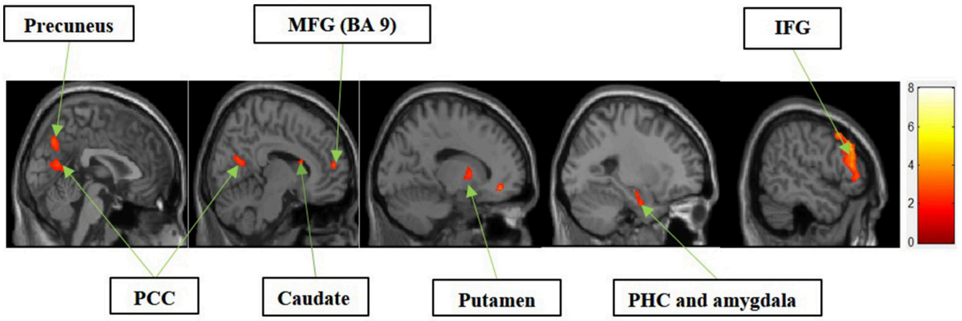

FIGURE 3 | Experiential motivation > functional motivation. The color bar reflects *t*-values that resulted from the contrast. The precuneus, PCC, MFG (Brodmann area 9), caudate, putamen, parahippocampal gyrus, amygdala, and IFG showed significantly higher activation while processing products with experiential motivation as compared to functional motivation.

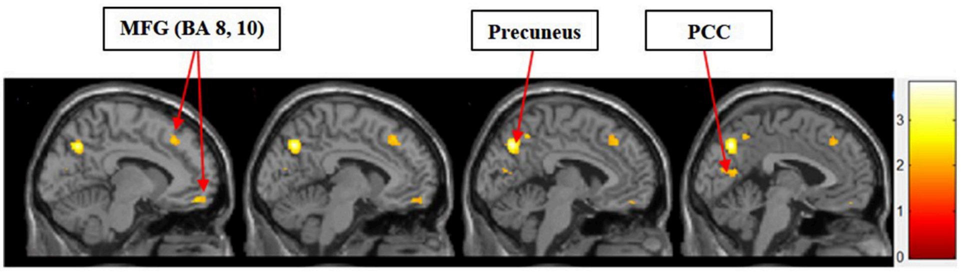

FIGURE 4 | Symbolic motivation > functional motivation. The color bar reflects *t*-values that resulted from the contrast. The MFG (Brodmann areas 8, 10), precuneus, and PCC showed significantly higher activation while processing products with symbolic motivation as compared to functional motivation.

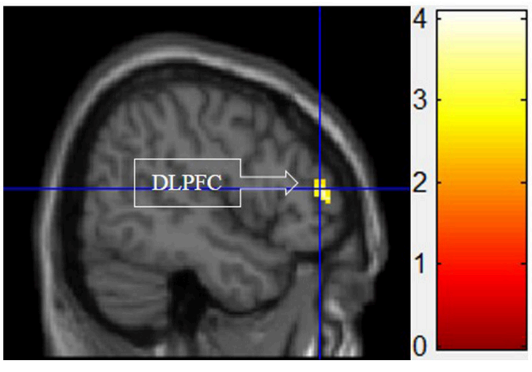

FIGURE 5 | Functional motivation > symbolic and experiential motivations. The color bar reflects *t*-values that resulted from the contrast. The DLPFC showed significantly higher activation while processing products with functional motivation as compared to both symbolic and experiential motivations.

and symbolic motivations. Experiential motivation activated the PCC, and a cluster containing the PHC and amygdala.

V. Symbolic Motivation > Functional and Experiential Motivations for Display

Figure 7 shows the results of *t*-tests for the contrast that compared symbolic motivation scenarios to the functional and experiential motivations. Symbolic motivation yielded significant activations in the MFG and IFG, as well as insula and posterior parietal cortex (PPC).

Detailed results of the group level voxel-wise analysis for contrasts of each of the three motivations, including peak MNI coordinates of the regions significantly activated (corrected $p < 0.05$), peak intensity (t-value), and cluster size (number of voxels) are reported in **Table 2**.

DISCUSSION

In the current study, we found that the MFG, precuneus, and PCC were differentially activated during both experiential and symbolic motivations (i.e., experiential motivation > functional motivation, see **Figure 3** and symbolic motivation > functional motivation, see **Figure 4**). These findings indicate that unlike functional motivation, both experiential and symbolic motivations appear to be related to self-reflection and self-relevant processing. This conclusion is consistent with prior implications that the MFG is related to self-reflection processing (Schaefer and Rotte, 2007). The activation of the putamen and caudate (see **Figure 3**) shows experiential motivation is related to a reward mechanism. In addition, the amygdala activation (see **Figure 3**) demonstrates experiential motivation led to emotional processing, which we did not find for symbolic motivation.

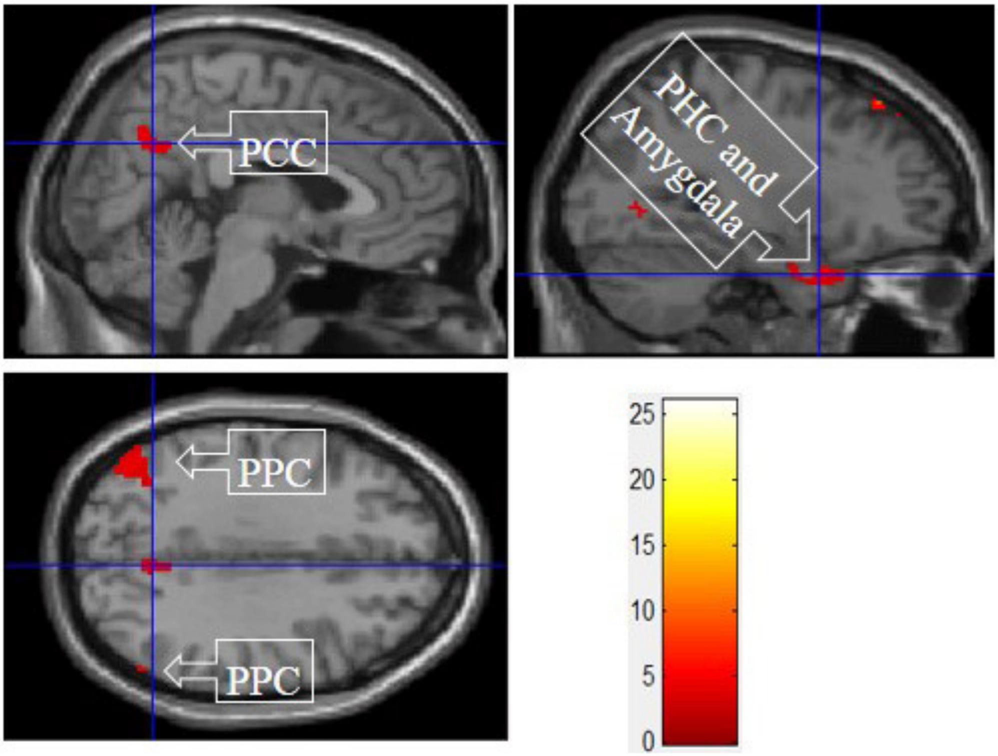

FIGURE 6 | Experiential motivation > symbolic and functional motivations. The color bar reflects *t*-values that resulted from the contrast. The PPC, parahippocampal gyrus, and amygdala showed significantly higher activation while processing products with experiential motivation as compared to both symbolic and functional motivations.

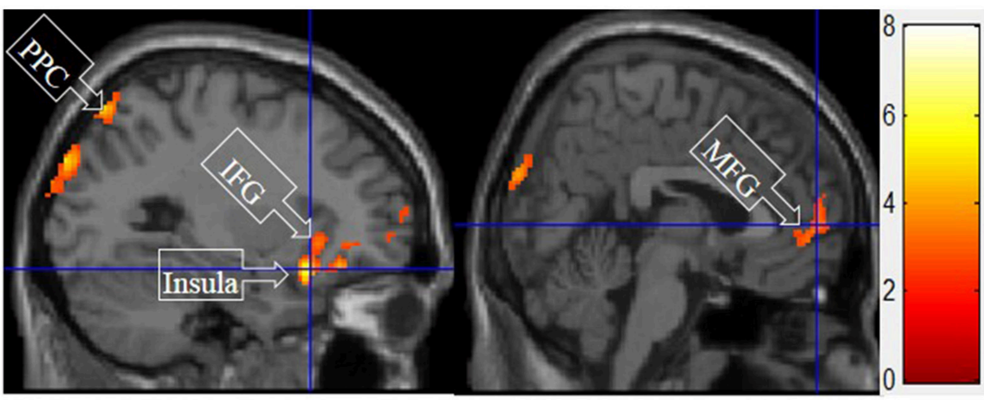

FIGURE 7 | Symbolic motivation > experiential and functional motivations. The color bar reflects *t*-values that resulted from the contrast. The PPC, IFC, insula, and MFG showed significantly higher activation while processing products with symbolic motivation as compared to both experiential and functional motivations.

As predicted, functional motivation demonstrated more activation in the DLPFC compared with other motivations (see **Figure 5**). The DLPFC has been widely studied and implicated in higher cognitive functions such as working memory, attention, decision-making, and executive control (O'Reilly, 2010). The current finding that functional motivation elicited the higher activation within the DLPFC is consistent with Keller's (1993) conceptual distinctions of this buying motivation, which is more associated with rational thoughts.

The consistent activation of the MFG, precuneus, and PCC suggested that there is no intrinsic difference between experiential motivation and symbolic motivation when contrasted with functional motivation. However, when experiential (or symbolic) motivation was contrasted against

TABLE 2 | Summary results from the functional contrasts of the motivation conditions.

Condition	Region	Peak MNI coordinate (*x*, *y*, *z*)	Peak intensity (*t*-value)	Cluster size (voxel #)
Experiential motivation> Functional motivation	Parahippocampal Gyrus	(−26, −6, −28)	2.42	72
	MFG	(16, 54, 10)	3.6	56
	Precuneus	(−4, −70, 40)	3.82	271
	Caudate	(12, 14, 16)	2.9	27
	PCC	(8, −64, 18)	2.8	126
	Putamen	(−16, 4, 2)	2.55	75
	IFG	(−56, 22, 8)	3.24	1017
Symbolic motivation > Functional motivation	MFG	(−10, 54, −14)	2.47	47
		(−8, 30, 44)	2.25	80
	Precuneus	(−2 ,−54, 50)	2.23	13
		(−2, −70, 42)	3.45	271
	PCC	(8, −64, 18)	2.8	126
Functional motivation > Experiential and Symbolic motivations	DLPFC	(48, 46, 10)	4.08	20
Experiential motivation > Functional and Symbolic motivation	PPC	(−46, −72, 24)	12.12	235
	PCC	(56, −66, 38)	4.75	32
		(6, −64, 36)	4.1	107
	Parahippocampal Gyrus	(32, 12, −32)	4.98	156
Symbolic motivation > Functional and Experiential motivation	Insula and IFG clusters	(36, 22, −20)	8.44	286
		(−30, 18, −16)	7.59	176
	PPC	(44, −84, 30)	9.17	283
	MFG	(14, 60, 2)	6.83	273

This table reports the results of the group level voxel-wise analysis for contrasts of each of the three buying motivations. Columns indicate condition, region, peak MNI coordinates, peak intensity (t-value), and cluster size (number of voxels).

both functional and symbolic (or experiential) motivations, respectively, the results demonstrated that the PCC was only found to be activated under experiential motivation (see **Figure 6**) and the MFG was found to be exclusively activated under symbolic motivation (see **Figure 7**). The PCC and MFG are two regions that are shown to be involved in self-referential thought processing (Ochsner et al., 2004; Vogt and Laureys, 2005). However, the PCC is associated with inward self-reflection aimed at comparing oneself with others (Benoit et al., 2010), while the MFG is associated with outward self-reflection aimed to better understand others (Johnson et al., 2006). Thus, the current results suggest that both experiential and symbolic motivations are associated with self-reflection processes; however, they involve unique neural mechanisms associated with differing social judgment-making processes. Specifically, experiential motivation appears to be associated with the PCC and inward comparisons of oneself to others. Alternatively, symbolic motivation is associated with the MFG and outward comparisons of oneself to others. Additionally, activation in the PHC suggests that experiential motivation elicits episodic memory as well as contextual associations (Aminoff et al., 2013). The amygdala activation also demonstrates that experiential motivation likely led to higher emotional processing than other motivations, consistent with the hedonic nature of experiential motivation. Unlike experiential and functional motivations, the activation during symbolic motivation in the insular cortex could be due to interoceptive awareness (Critchley et al., 2004).

These findings are consistent with previous findings and our hypotheses, with the exception that there was no evidence of reward mechanisms being involved in the regulation of social relations such as dominance and social rank (Erk et al., 2002); instead, only experiential motivation was related to reward regions (i.e., caudate, putamen). These results are not without limitations. First, an experimenter error resulting in the loss of button responses during the task precludes strong evidence supporting notions that participants imagined the exact buying scenarios that they were instructed to maintain while viewing the product stimuli. However, it is unlikely that participants would disregard the instructions as they did not report any difficulty after the tasks were completed. A second limitation is the likelihood that imagining buying scenarios only simulates these otherwise intrinsic factors that arise from ecological consumer decisions. Although studies that examine such ecological buying scenarios would provide an alternative assessment to the current study, the level of control that provided the current results enabled maximal statistical power and spatial localization given the goals of the current study. A final limitation worth noting is the relatively small sample size in this study ($n = 10$). The current study serves as a preliminary neuroimaging assessment of neural correlates that vary between functional, experiential, and symbolic buying motivations. Accordingly, the findings of the current study serve as an initial assessment for the neural basis of consumer buying motivations and warrant further investigations with larger sample sizes to enhance the validity of the findings.

Notwithstanding these limitations, the current results shed light on the neural basis of consumer buying motivations. Importantly, we demonstrated functional dissociations consistent with reported models of distinct buying motivations (Keller, 1993). Within each condition of the current study, clusters of activation implicated neural correlates that were previously associated with specific types of information processing. The functional correlates implicated were largely in line with the understanding of the contributions of information processing that are said to underlie each motivational factor. Namely, functional buying motivation was associated with previously implicated cognitive control regions of the PFC (i.e., DLPFC), suggesting that such cognitive control might be suppressed under the experiential or symbolic buying conditions, potentially leading to less rational decision making.

An unexpected result was the common activation for both experiential > functional motivation and symbolic > functional motivation within the PCC and MFG. An interesting caveat to this common activation is that these buying motivations differed in activation when contrasted against every other condition. Specifically, the PCC was activated exclusively with the experiential motivation conditions, whereas the MFG was activated exclusively with the symbolic motivation condition. These findings may provide the neural basis of how self-referential valuations elicited by experiential and symbolic motivations are likely similar, yet different in subtle ways. Experiential motivation is elicited when consumers seek emotional benefits of consumption to fulfill hedonic needs (Keller, 1993). Thus, the high activation in the PCC as well as amygdala, putamen, and caudate with experiential motivation suggests that reward mechanism associated with episodic memory-based emotional arousal may guide internalizing self-reflection and comparisons under this motivation. On the other hand, symbolic buying motivation is elicited when consumers pursue social approval or self-enhancement in social settings (Keller, 1993). Thus, the high activation in the MFG with symbolic motivation suggests the instrumental, goal-directed nature of externalizing self-reflection and comparisons under this motivation. By examining the neural basis for different types of consumer buying motivations, this study contributes to enhancing the understanding of how consumer choices are made and why varying levels of self-control may be exerted under different buying motivational states.

ETHICS STATEMENT

This study was carried out in accordance with the recommendations of the Auburn University Institutional Review Board with written informed consent from all subjects. All subjects gave written informed consent in accordance with the Declaration of Helsinki. The protocol was approved by the Auburn University Institutional Review Board.

AUTHOR CONTRIBUTIONS

AG collected the data. YW analyzed the data. AG and YW prepared the manuscript. WK, SB, JK, and GD provided the design of the study, supervision, and revisions on various drafts of the manuscript. AG revised the manuscript.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: http://journal.frontiersin.org/article/10.3389/fnins.2017.00512/full#supplementary-material

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They Are What You Hear in Media Reports: The Racial Stereotypes toward Uyghurs Activated by Media

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Stereotypes from the major nationality toward minorities constitute a widely concerning problem in many countries. As reported by previous studies, stereotypes can be activated by media information that portrays the negative aspects of the target group. The current study focused on the neural basis of the modulation of negative media information on Han Chinese stereotypes toward Uyghurs by using event-related potentials. We employed the lexical decision task, in which participants were asked to categorize the presented word as positive or negative. Behavioral result showed that participants had a shorter reaction time to positive adjectives than to negative adjectives. The data of brain activity showed that compared with the Han condition, the Uyghurs condition elicited smaller N400 differences in the media priming group, whereas there was no significant N400 deflection difference between Han Chinese and Uyghurs in the control group. The current results suggested that the negative media information might influence their judgments toward other groups reflected in the deflection of N400 amplitude. Therefore, in order to mitigate or even eliminate stereotypes about national minorities, the effort of the media is important.

Keywords: stereotypes, ERPs, Uyghurs, N400, Han Chinese, media

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INTRODUCTION

Individuals' negative stereotypes toward outgroup individuals may lead to social problems, such as race bias between nationalities, which has been commonly reported by previous studies. For instance, Whites' prejudice toward Blacks has been widely investigated by researchers (e.g., Crosby et al., 1980). Dovidio and colleagues conducted an experiment to study Whites' stereotypes toward Blacks by investigating the association between schematic faces of Black/White and positive/negative words. Their results showed that the White participants responded faster to positive words but slower to negative words following a White prime vs. following a Black prime. The authors explained it as the result of Whites' stereotypes toward Blacks (Dovidio et al., 1997).

Similar to America, China is a multinational country. As Han people make up 93% of the Chinese population, their attitude toward other national minorities is of great importance for social stability. Thus, many researchers focused on the racial prejudice phenomenon in China, especially the images and social distance among Han Chinese, minorities and foreign nationalities. For example, Fong and Spickard (1994) studied ethnic relations in China. Their results showed that Han Chinese felt affinity for overseas Chinese and Uyghurs but felt extreme distance from Tibetans (Fong and Spickard, 1994). Yee (2003) conducted fieldwork in Urumqi, the provincial capital of

Xinjiang Uyghur Autonomous Region, to study ethnic relations and found there was a low degree of integration between the two ethnic groups (Yee, 2003).These studies showed the existence of negative stereotype between nationalities in China. It is natural to ask if there are any ways to change or eliminate the negative stereotype.

Based on the social category theory, stereotypes derived from category-based responses to other people on the basis of social distinctions such as race, gender, and age (Bodenhausen and Macrae, 1998; Fiske et al., 1999). Therefore, people are motivated to overcome the stereotypes by avoiding responding to targets primarily on the basis of a category (Fiske and Neuberg, 1990; Plant and Devine, 1998). Categorization happens often based on the visually prominent and culturally relevant features (Brewer and Feinstein, 1999). As culturally relevant features are hard to be changed, the prominent visual information is always adapted to change or eliminate the stereotype. It was suggested that exposure to stereotype-associated stimuli may activate the stereotype. This may be applied generally to the perceptions and evaluations of outgroup others (Bargh et al., 1996; Lepore and Brown, 1997). Specifically, the available stereotypic information tends to lead to stereotype application in subsequent judgments of stereotyped group members (Henderson-King and Nisbett, 1996).

Previous studies have shown that media, which is a main source of external information, played an important role in stereotype activation. For instance, researchers have suggested that depictions of African Americans as criminal, aggressive, and unintelligent in the media help reinforce and maintain hostile anti-black prejudice against this African Americans (Oliver, 1999; Dixon and Linz, 2000). Similarly, researchers also found that when the Western media portrayed third-world people as naive, inferior, traditional, and uncivilized, it rationalized the perpetuation of benevolent, paternalistic prejudice toward these people (Mitra, 1999; Ramasubramanian, 2005). There were also studies which tried to employ the media to reduce intergroup prejudice (Ramasubramanian, 2007; Paluck, 2009). Therefore, in the current study, we intend to investigate whether there are also racial biases and stereotypes in China and if these biases and stereotypes will be impacted by the media. Specifically, we focus on Han's attitude toward Uyghurs, which is one of the main national minorities in China, and how media information influences this effect.

In comparison to the descriptive research on media stereotypes, relatively few studies had investigated the cognitive processes involved in media stereotyping. Some sociologists have applied research techniques from cognitive neuroscience, such as eye-tracking, functional magnetic resonance imaging (fMRI) and event-related potentials (ERPs), to investigate the cognitive processes of racial prejudice and stereotyping in recent years (Payne, 2001; Amodio et al., 2004; Correll et al., 2006). For example, Wang et al. (2011) investigated the stereotypes about rural migrant workers (RMW) in China by using event-related potentials and found the RMW-positive adjective condition elicited larger N400 amplitude than the urban worker-positive adjective condition, which revealed the negative stereotypes about RMWs (Wang et al., 2011). Therefore, in the current study, we also intend to employ ERPs to investigate the cognitive processes of media stereotyping of Han Chinese toward Uyghurs on brain level.

Based on previous ERPs studies about stereotyping (White et al., 2009; Hehman et al., 2014), the N400 is considered as the index of stereotypes. The N400 component was first studied by Kutas and Hillyard (1980) by using an anomalous sentence task. They found that the N400 was a negative ERP deflection that appeared when there was semantic incongruity of a sentence and typically peaked around 400 ms at central-parietal electrode sites (Kutas and Hillyard, 1980). In subsequent studies, researchers also found that the N400 could be elicited by semantic incongruity of word pairs (Franklin et al., 2007). That is, when the second word had no semantic relationship with the first word, it elicited larger N400 amplitude. Additionally, researchers have suggested that a stereotype can also be defined as a specific class of semantic association sorted by memory (Amodio et al., 2008; White et al., 2009). Therefore, a lexical decision task is often used to study stereotypes and racial prejudice, and the N400 component is considered as a neural index. For example, in a study by White et al. (2009), participants were primed by a gender category (Women or Men) followed by a word that was either consistent or inconsistent with a gender stereotype. The stereotype-incongruent word pairs elicited larger N400 amplitudes compared to the stereotype-congruent word pairs (White et al., 2009).

Based on the aforementioned literatures, we believed that semantic mismatch in the lexical decision task would affect the amplitude of the N400 and possibly reveal a stereotype effect. Specifically, the incongruity between the meaning of the second stimuli and the first stimuli would elicit larger N400 amplitude than the congruent condition. On the other hand, according to previous studies about media effect of stereotype, we hypothesized that Han's stereotypes toward Uyghurs would be enhanced by negative media information about Uyghurs. Thus, we expected that the incongruity between Uyghurs and positive adjectives would be larger and/or the congruity between Uyghurs and negative adjectives would be smaller in the media priming group. That is, compared with the control group, the N400 amplitude induced by negative adjectives would be smaller and/or the N400 amplitude induced by positive adjectives would be larger under the Uyghurs condition in the negative media priming group. This phenomenon may not be found under the Han condition since no negative media information about Han was provided. In order to state the results more clearly, we intend to extract the N400 difference wave by minus the positive adjectives condition from the negative adjectives condition. Therefore, smaller d-N400 means participants considered the previous shown photo more incongruent with positive adjectives and/or more congruent with negative adjectives. This suggested the larger degree of negative stereotypes toward Uyghurs. Therefore, we hypothesized the d-N400 between negative adjectives and positive adjectives following Han Chinese would be larger than those following Uyghurs after priming with negative media information. The hypotheses are also summarized in the following **Table 1**.

METHODS

Participants

In all, 36 graduate or undergraduate students (18 male) were recruited from Zhejiang University, ranging in age from 20 to 27 years old (mean age = 23.03; SD = 1.70) to participant the EEG experiment. Another 50 graduate or undergraduate students (25 male) were recruited, ranging in age from 20 to 27 years old (mean age = 23.03; SD = 1.70) to participant in the same experiment behaviorally without recording their EEG data. They were all of Han nationality. Their mother tongue was Mandarin Chinese. They self-reported right-handedness. Participants had normal or corrected-to-normal vision, and they were screened for a history of neurological and psychiatric disorders, substance abuse, and current psychotropic medications. The participants were assigned randomly to two groups (priming vs. control) before the event-related potentials (ERPs) experiment. For the EEG experiment, in each group, there were 18 participants (9 males). For the behavioral experiment, there were 43 participants (22 males) in each group. Informed consent was obtained from all participants, and the research was approved by the Ethical Committee of the Neuromanagement Lab of Zhejiang University. All the participants claimed to have unprejudiced attitudes toward the Uyghur nationality, and they were paid 35 RMB for participation. The data from one subject in the priming group were discarded for excessive recording artifacts, and the data from one subject in the control group were discarded for misunderstanding the rules of the categorization task, resulting in low accuracy (56.67%). Thus, 34 valid subjects were included in the final EEG data analysis and 84 valid subjects were included in the final behavioral data analysis.

Stimuli and Procedures

The stimuli consisted of 240 image-word pairs (12 facial images × 20 adjectives) divided randomly into 4 blocks. We obtained facial images from graduates (with their permission to be used in this study) of the Xinjiang University, which is located in the Xinjiang Uyghur Autonomous Region. Six facial images were of individuals of Uyghur nationality (half male and half female), and another six were of individuals of Han nationality (half male and half female). The images were unfamiliar to the participants (no schoolmates or celebrities) and were edited by Adobe Photoshop 10.0 (Adobe Systems Incorporated, San Jose, California, USA) to a uniform size (4.23 cm by 6 cm, 240 by 340 pixels). After the experiment, participants were asked to classify the 12 facial images into two groups, the "Uyghur nationality" group or the "Han nationality" group. All of them gave the correct answer. The 20 adjectives (half positive and half negative) were derived from Wang et al. (2011)and are shown in **Table 2**. The 240 image-adjective pairs were divided into four conditions: Uyghur nationality-positive adjective, Uyghur nationality-negative adjective, Han nationality-positive adjective, and Han nationality-negative adjective.

TABLE 1 | Summary of hypotheses for N400 and d-N400 amplitudes.

Group	Stereotype	Hypotheses for N400 amplitude	Hypotheses for d-N400 amplitude
Control	No difference between two nationalities	Negative adjective> Positive adjective for both nationalities	No significant difference for d-N400 amplitude of the two nationalities
Priming	Stereotype was activated only in Uyghur condition but not in Han Chinese condition	Han condition: negative adjective>positive adjective, almost the same as control group Uyghur condition: negative adjective induced similar or even smaller N400 than positive adjective	Han >Uyghur

PROCEDURE

Participants were comfortably seated in a dim, sound-attenuated and electrically shielded room. The instructions for the experiment were presented on written paper. The experimental stimuli were presented in the center of a computer-controlled CRT monitor at a distance of 100 cm (with a visual angle of $2.42° \times 3.44°$). All the stimuli, recording triggers, and behavioral responses were presented and recorded with the E-Prime 2.0 software package (Psychology Software Tools, Pittsburgh, Pennsylvania, USA). A keypad was provided to the participants to make choices. Participants were informed that they would see a series of image-word pairs and their task would be to categorize the word as positive or negative as quickly as possible. The experiment included four blocks for both the priming and control group with each block included 60 trials.

A single trial is shown in **Figure 1**. In each trial, a central fixation cross was presented for a duration varying randomly between 600 and 800 ms. Then, the facial image was presented at the center of the screen for 2,000 ms against a white background. After a random blank screen that lasted for 600–800 ms, the Chinese adjective was shown. The participant pressed one of two keys to indicate their classification. The response key corresponding to positivity or negativity was counterbalanced across participants. The trials were presented randomly, and the interval across trials was 1,000 ms.

Prior to the initiation of the formal experiment, each participant practiced five trials to familiarize themselves with the procedure. More importantly, there was a one-minute-long video show before the formal experiment for the priming group but not for the control group. The video was derived from a television program about ethnic clashes between the Uyghur

TABLE 2 | Selected Chinese adjectives translated into English.

Positive adjectives	Negative adjectives
confident, righteous, civilized, polite, elegant, wise, noble, gentle, decent, and dignified	dirty, clumsy, shortsighted, rude, lazy, mean, extreme, narrow-minded, stingy, and barbaric

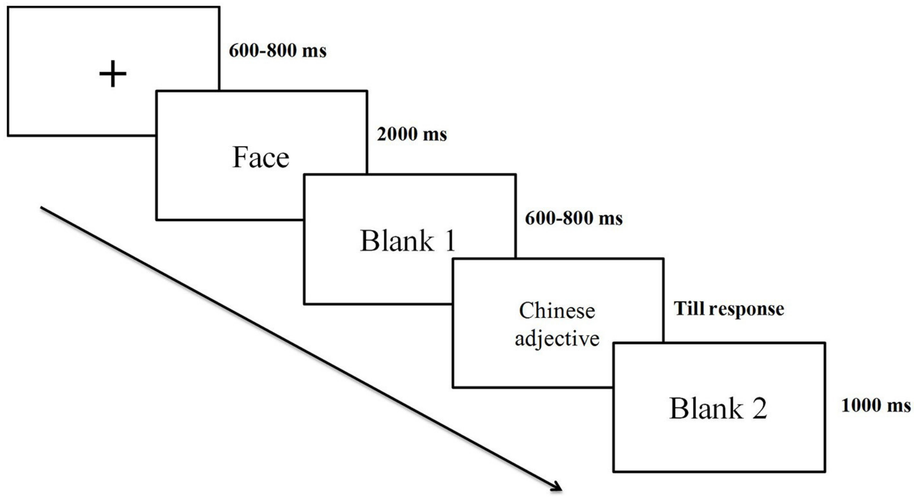

FIGURE 1 | Experimental task: Participants were instructed to categorize the word as positive or negative. EEGs were recorded from the subjects throughout the experiment.

nationality and Han nationality in Urumqi on July 5th, 2009. It reported there was a series of violent riots in Urumqi, which began as a protest of Uyghurs but escalated into violent attacks that mainly targeted Han people. Some Hans died. Many vehicles and buildings destroyed.

EEG Recording

The EEG was recorded (band-pass 0.05–70 Hz, sampling rate 500 Hz) with a Neuroscan Synamp2 Amplifier (Scan 4.3.1, Neurosoft Labs, Incorporated, Sterling, Virginia, USA) using an electrode elastic cap (64 Ag/AgCl electrodes according to the standard international 10–20 system). A frontal electrode site between FPz and Fz was used as the ground. There were two mastoid electrodes, and the left was used as a reference. Horizontal and vertical electrooculograms (EOG) were monitored with two pairs of electrodes, one pair located below and above the left eye in parallel with the pupil, and the other pair situated 10 mm from the lateral canthi. The experiment started only when the electrode impedances were kept under 5 kΩ.

EEG/ERP Data Analyses

The EEG data were analyzed using Neuroscan 4.3.1. Data were re-referenced to the algebraically computed average of the left and right mastoids for further analysis. The EOG artifacts with ocular movements were corrected using the algorithm proposed by Semlitsch et al. (1986). The EEGs were digitally low-pass filtered at 30 Hz (24 dB/Octave) and were segmented into epochs from 200 ms before stimulus onset to 1,000 ms after stimulus onset. Baseline correction was performed with the first 200 ms of each channel. Trials that contained amplifier clipping, bursts of electromyography activity, or peak-to-peak deflections that exceeded $\pm 80\ \mu V$ were excluded from the final average. More than 40 sweeps for each condition remained. During facial image presentation, the EEG epochs were averaged for the ethnic Han's face and the ethnic Uyghur's face. During the Chinese adjective presentation, the EEG epochs were separately averaged for nationality (Han/ Uyghur) and adjective (positive/negative).

STATISTICAL ANALYSIS

For the behavioral data analysis, the response accuracy and the reaction times for correct responses to adjectives were separately analyzed with a 2 (nationality: Han vs. Uyghur) × 2 (adjective: positive vs. negative) × 2 (group: priming vs. control) mixed-design repeated-measures ANOVA.

In further EEG analysis, we chose the time window from 320 to 430 ms after the adjective onset to analyze the mean amplitude of the N400 on the basis of the visual observation of the grand average waveforms and on the guidelines provided by Picton et al. (2000). We selected nine electrode sites for the statistical analysis: F1/z/2, C1/z/2, and P1/z/2 in frontal, central and parietal areas. We carried out a 2 (nationality: Han vs. Uyghur) × 2 (group: priming vs. control) × 2 (adjective: positive vs. negative) × 9 (electrode: F1/z/2, C1/z/2, and P1/z/2) mixed-design repeated-measures ANOVA for N400 analysis. Similarly, a 2 (nationality: Han vs. Uyghur) × 2 (group: priming vs. control) × 9 (electrode: F1/z/2, C1/z/2, and P1/z/2) mixed-design repeated-measures ANOVA for differentiated N400 analysis (d-N400: negative/positive N400 discrepancy, which reflects the degree of bias) was also conducted. A simple-effect analysis was carried out when any significant interaction effect among factors appeared. The Greenhouse–Geisser correction was applied in all statistical analyses when necessary (Greenhouse and Geisser, 1959).

RESULTS

Behavioral Results

For the 2 (nationality) × 2 (adjective) × 2 (group) mixed-design ANOVA of response accuracy, no significant main effect or interaction effect for these factors was found ($ps > 0.05$). For the 2 (nationality) × 2 (adjective) × 2 (group) mixed-design ANOVA of reaction time, the results showed a significant main effect of adjective [$F_{(1, 82)} = 19.181$; $p < 0.01$; $\eta^2 = 0.190$], which indicated that participants had a shorter reaction time toward positive adjectives ($M = 753.419$ ms, S.E. = 26.264) than toward negative adjectives ($M = 784.982$ ms, S.E. = 26.689). The main effect of nationality was marginally significant [$F_{(1, 82)} = 3.770$; $p = 0.056$; $\eta^2 = 0.044$], and the reaction time toward the Uyghur nationality ($M = 777.049$ ms, S.E. = 29.030) was longer than the Han nationality ($M = 761.352$ ms, S.E. = 23.793). However, no significant main effect was found by group ($p > 0.05$). There was also no interaction effect among these factors ($ps > 0.05$). All the results were summarized in **Table 3**.

ERP Results

N400 Analysis

For the 2 (nationality) × 2 (group) ×2 (adjective) ×9 (electrode) mixed-design ANOVA of N400, the results showed no significant main effects ($ps > 0.1$) for nationality and group. The interaction effect of nationality and group, nationality and adjective as well as adjective and group were not significant ($ps > 0.1$). However, the main effect of adjective [$F_{(1, 32)} = 52.279$; $p < 0.001$; $\eta^2 = 0.620$] as well as the interaction effect of nationality, adjective and group was notable [$F_{(1, 32)} = 5.178$; $p = 0.030$; $\eta^2 = 0.139$].

Therefore, simple-effect analyses were conducted. In the priming group, the main effect of nationality was not significant ($p > 0.1$). The main effect of adjective [$F_{(1, 16)} = 26.017$; $p < 0.001$; $\eta^2 = 0.619$] and interaction effect of nationality and adjective [$F_{(1, 16)} = 13.127$; $p = 0.002$; $\eta^2 = 0.451$] were notable. Further simple-effect analyses were also conducted. For the Han nationality, the negative adjective ($M = -1.147$ μV, SE = 0.536) induced larger N400 amplitude than that of positive adjective ($M = 1.018$, μV, SE = 0.609). However, there was no significant N400 difference for negative and positive adjective under the Uyghur condition. In the control group, only the main effect of adjective was significant [$F_{(1, 16)} = 27.008$; $p < 0.001$; $\eta^2 = 0.628$]. The main effects of nationality as well as the interaction effect of nationality and adjective were not significant ($ps > 0.1$).

TABLE 3 | F statistics and *p*-value of behavioral results.

Source	Response accuracy		Reaction time	
	F	*p*-value	*F*	*p*-value
nationality	2.785	0.099	3.770	0.056
adjective	0.872	0.353	19.181	<0.001
group	0.079	0.780	0.663	0.418
nationality* adjective	1.604	0.209	0.283	0.596
nationality* group	0.988	0.323	1.269	0.263
adjective* group	0.723	0.398	3.274	0.074
nationality* adjective* group	0.114	0.737	2.680	0.105

N400 Difference Wave Analysis

In order to descript the results more clearly, the N400 difference wave was also analyzed. For the 2 (nationality) × 2 (group) × 9 (electrode) mixed-design ANOVA of d-N400, the results showed no significant main effects ($ps > 0.05$). However, the interaction effect of nationality and group was significant [$F_{(1, 32)} = 5.178$; $p = 0.030$; $\eta^2 = 0.139$]. Further simple-effect analysis indicated that, in the priming group [$F_{(1, 16)} = 13.127$; $p = 0.002$; $\eta^2 = 0.451$], the Uyghur nationality ($M = -0.655$ μV, SE = 0.328) induced a significantly less negative d-N400 than that of the Han nationality ($M = -2.165$ μV, SE = 0.364), but there were no significant d-N400 differences between the Uyghur nationality ($M = -2.023$ μV, SE = 0.551) and the Han nationality ($M = -1.671$ μV, SE = 0.448) in the control group ($p > 0.1$). When only the Uyghur nationality was analyzed, the effect of group was significant [$F_{(1, 32)} = 4.545$; $p = 0.041$; $\eta^2 = 0.124$], and the mean d-N400 in the priming group ($M = -0.734$ μV, SE = 0.303) was less negative than that in the control group ($M = -1.504$ μV, SE = 0.611). There were no significant d-N400 differences between the priming group ($M = -1.958$ μV, SE = 0.360) and the control group ($M = -1.707$ μV, SE = 0.402) when only the Han nationality was analyzed ($p > 0.1$), as shown in **Figure 2**.All the results of N400 amplitude and d-N400 in the different conditions are summarized in **Table 4**.

DISCUSSION

Using ERP measurements, the present study performed a brain-level analysis of the mechanism underlying modulation of negative media reports on Han Chinese stereotypes toward a national minority, the Uyghurs. A lexical decision task was conducted in two groups, control group and media priming group.

Behavioral results showed that participants had a shorter reaction time to positive adjectives than to negative adjectives. Previous studies about stereotypes have suggested that the accessible attitudes are faster at recognizing stereotypical words. As a result, the incongruent condition would have longer reaction time than the congruent condition (Fazio et al., 1995; Dovidio et al., 1997). Therefore, the current result revealed that for the impression of both Uyghurs and Han Chinese, positive adjectives are more congruent.

At the brain level, we found that the N400 difference induced by negative adjectives and positive adjectives was similar between two nationalities in the control group. However, in the media priming group, the Uyghur nationality induced a significantly less negative d-N400 than the Han nationality. That is, compared with the Han nationality, the N400 difference induced by the negative adjective and the positive adjective was smaller toward the Uyghur nationality. More specifically, after the negative priming from media information, the N400 amplitude induced by negative adjectives became smaller and/or the N400 amplitude induced by positive adjectives became larger under the Uyghurs condition compared with the control group. These results are in accordance with our hypotheses which are summarized in **Table 1**. According to the above-mentioned literatures on the

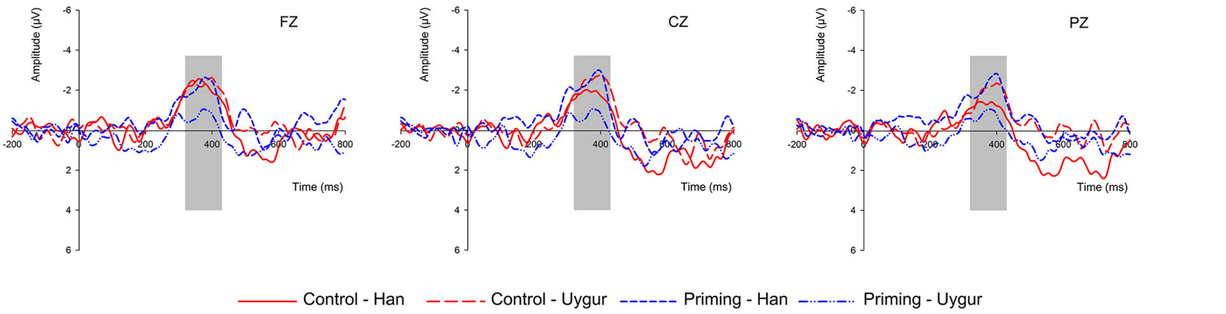

FIGURE 2 | Grand-averaged ERP waveforms in the whole brain regions with three electrodes: Fz, Cz, and Pz. N400 difference comparison between the two groups (media priming group vs. control group) and two nationalities (Han vs. Uyghur). The time window for the d-N400 was 320–430 ms.

TABLE 4 | Amplitudes and statistic results of N400 and N400 difference wave.

Group	Experiment condition	N400 amplitude (μV)	N400 difference amplitude(μV)	Simple-effect analysis pair	Result
Control	Han negative (HN)	−0.598	−1.671	Control: HN vs. HP for N400	N/A
	Han positive (HP)	1.103		Control: UN vs. UP for N400	N/A
	Uyghur negative (UN)	−1.126	−2.023	Priming: HN vs. HP for N400	Negative> Positive
	Uyghur positive (UP)	0.897		Priming: UN vs. UP for N400	Not significant
Priming	Han negative (HN)	−1.147	−2.165	Control: Han vs. Uyghur for d-N400	Not significant
	Han positive (HP)	1.018		Priming: Han vs. Uyghur for d-N400	Han > Uyghur
	Uyghur negative (UN)	−0.390	−0.655	Han: Control vs. Priming for d-N400	Not significant
	Uyghur positive (UP)	0.265		Uyghur:Control vs. Priming for d-N400	Control> Priming

N400, the N400 deflection can be considered an index of stereotypes (Rasmussen, 2007; White, 2008; Hehman et al., 2014). Therefore, the current results suggest that negative stereotypes only occurred when the participants had been primed with negative information about Uyghurs. This was consistent with previous studies which stated that the related negative media information could increase the stereotype effect. For example, an early study on gender stereotypes showed that stereotypic rock music videos increased the accessibility of sex role stereotypic schemas (Hansen and Hansen, 1988). This study supported the notion that the media information could enhance the gender stereotype effect. Furthermore, some studies also showed that media information could also influence stereotype effect toward another nationality. Such as, a study conducted by Givens and Monahan examined how mediated portrayals of African American women influenced judgments of them. Their results showed that when evaluating a job interviewee, the jezebel stereotype video increased participants' negative perception toward African American females (Givens and Monahan, 2005).

Researchers also tried to explain this phenomenon theoretically. The model of stereotype activation suggested by Devine and Montiethstated that certain circumstances influence the stereotype effect even though the stereotypes are always activated unintentionally and unconsciously (Devine and Monteith, 2009). That is, without conscious efforts to rectify them, frequent and recent exposure to stereotypes in the environment will more easily influence perceivers' social judgments and impressions about the racial group (Wittenbrink et al., 2001). As what we stated in the introduction part, the category response is related to existing stereotypes. The racial categorization will be enhanced by available visual information (the priming video, in this case) since the presence of priming information facilitates responses to target categories that share meaning, valence, or some other key attribute (Neely, 1977). The associations between race categories and certain attributes are believed to be largely automatic (Fiske, 1998), learned through first-hand experiences with people of the stereotyped groups and second-hand external information, such as the media (Ramasubramanian, 2007). When there is lack of first-hand experiences, the second-hand external information becomes an important consideration for the participants' attitudes toward another group.

In the current study, the participants are Han Chinese from the Zhejiang province, which is far from the Uyghur's community, Urumqi. They have little or even no direct contact with Uyghurs. As a result, their perception of Uyghurs mainly comes from vicarious contact through the media. Thus, the biased information from the media inevitably becomes incorporated into "common knowledge" or schemata that viewers form about Uyghurs. In the media priming group, the participants were exposure in negative media information of Uyghurs, their negative stereotype toward Uyghurs was enhanced, resulting in smaller N400 difference between negative adjective and the positive adjective. These results add to the findings of a number of related studies (Amodio et al., 2004; Conrey et al., 2005) by clarifying one manner in which available information can activate category responses.

However, there are also some limitations in the current study. Firstly, the current study only focused on the negative aspect of media information. Future research can also focus on the positive aspect of media information and develop strategies to mitigate or even eliminate the stereotypes of biased media about national minorities. Secondly, the participants of the current studies are university students, who have little first-hand experiences with Uyghurs. Future studies can focus on the participants who are more familiar with the Uyghurs and investigate if their stereotype would also be activated by negative media information. Thirdly, using one video for induction purposes may not be reliable enough. In the future, researchers can consider using at least 2 or 3 examples of stimuli for such purposes and check that the effect is similar for all of them. Last but not the least, the current study only concerned about the negative media portrayals influences the perception of minorities, but ignored the other social groups. Future studies can investigate this effect by adding a third condition in which the same negative induction scenario is addressed toward the other individuals.

In summary, the current study investigated the associated underlying neural mechanisms of Han Chinese media stereotype toward a national minority, the Uyghurs. The behavioral results showed that participants have a longer reaction time under the positive adjective condition compared to the negative adjective condition regardless of the nationality presented. The ERPs results indicated that compared with Han people, the Uyghurs elicited smaller N400 difference in the media priming group, but this effect was not found in the control group. As N400 amplitude can be modulated by stereotype effect, the current results suggested that when Han Chinese were primed by negative information about a specific group from the media, their negative stereotypes toward people from the target group were activated. That is, the media can influence people's judgments toward other groups in subtle, subconscious ways.

AUTHOR CONTRIBUTIONS

JJ made substantial contributions to the conception of the work, analysis, and interpretation of data, as well as drafting the manuscript. GP made substantial contributions to the conception of the work, as well as data acquisition, data interpretation. QM made substantial contributions to the conception of the work, as well as the analysis and interpretation of data. All authors gave approval of the final version.

ETHICS STATEMENT

This study was carried out in accordance with the recommendations of the Ethical Committee of the Neuromanagement Lab of Zhejiang University with written informed consent from all subjects. All subjects gave written informed consent in accordance with the Declaration of Helsinki. The protocol was approved by the Ethical Committee of the Neuromanagement Lab of Zhejiang University.

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Corrigendum: They Are What You Hear in Media Reports: The Racial Stereotypes toward Uyghurs Activated by Media

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Characteristics of Human Brain Activity during the Evaluation of Service-to-Service Brand Extension

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Brand extension is a marketing strategy to apply the previously established brand name into new goods or service. A number of studies have reported the characteristics of human event-related potentials (ERPs) in response to the evaluation of goods-to-goods brand extension. In contrast, human brain responses to the evaluation of service extension are relatively unexplored. The aim of this study was investigating cognitive processes underlying the evaluation of service-to-service brand extension with electroencephalography (EEG). A total of 56 text stimuli composed of service brand name (S1) followed by extended service name (S2) were presented to participants. The EEG of participants was recorded while participants were asked to evaluate whether a given brand extension was acceptable or not. The behavioral results revealed that participants could evaluate brand extension though they had little knowledge about the extended services, indicating the role of brand in the evaluation of the services. Additionally, we developed a method of grouping brand extension stimuli according to the fit levels obtained from behavioral responses, instead of grouping of stimuli *a priori*. The ERP analysis identified three components during the evaluation of brand extension: N2, P300, and N400. No difference in the N2 amplitude was found among the different levels of a fit between S1 and S2. The P300 amplitude for the low level of fit was greater than those for higher levels ($p < 0.05$). The N400 amplitude was more negative for the mid- and high-level fits than the low level. The ERP results of P300 and N400 indicate that the early stage of brain extension evaluation might first detect low-fit brand extension as an improbable target followed by the late stage of the integration of S2 into S1. Along with previous findings, our results demonstrate different cognitive evaluation of service-to-service brand extension from goods-to-goods.

Keywords: service brand, brand extension, electroencephalography, event-related potential, neuromarketing

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INTRODUCTION

Brand extension refers to a marketing strategy where a well-established brand extends its name to new goods or services (Loken and John, 1993). Since its first introduction in 1960s, brand extension has been widely employed as an effective brand marketing strategy (Gamble, 1967; Tauber, 1988). Brand extension can elevate brand equity by increasing brand loyalty as well as reducing the entry barrier and advertising costs (Tauber, 1981, 1988; Aaker and Keller, 1990), while it can also entail risks that the failure of extension does harm to the well-established parent brand images (Boush and Loken, 1991; Loken and John, 1993; Gürhan-Canli and Maheswaran, 1998; John et al., 1998) and possibly create undesirable associations with the brand in the consumers' mind (Aaker and Keller, 1990). Therefore, it is important to understand cognitive and behavioral aspects of consumers' evaluation on brand extension for developing a successful brand extension strategy.

Goods and service are considered as both sides of an important continuum of "offering," being distinguished from each other by the characteristics such as inseparability, heterogeneity, intangibility, perishability, and a lack of ownership (Zeithaml et al., 1985; Iacobucci, 1998; Lovelock and Gummesson, 2004). Based on this offering level, brand extension can be separated into four types: goods-to-goods, goods-to-service, service-to-service, and service-to-goods (Ramanathan, 2013).

Several behavioral evaluation methods have been proposed to measure the success of extension using explicit survey responses (Völckner and Sattler, 2006; Arslan and Altuna, 2012) or implicit eye tracking movements (Stewart et al., 2004). They showed that a "fit" between a parent brand and extension goods is the most crucial factor for successful brand extension (Aaker and Keller, 1990; Völckner and Sattler, 2006). Therefore, measuring a fit is one of the indicators related to how successful brand extension would be. However, the information provided by the behavioral methods is often limited to account for cognitive processes underlying brand extension evaluation. Alternatively, recent advances in neuroscience have enabled direct measurements of brain activities associated with cognitive processes, providing opportunities to understand cognitive evaluation of brand extension. Hence, using a neuroscience approach, marketers may be able to choose new goods/services with an appropriate fit level for successful brand extension.

A number of neurophysiological studies, mostly using electroencephalography (EEG), have revealed neural activities related to the evaluation of brand extension (Ma et al., 2007, 2008, 2010, 2014a,b; Wang et al., 2012; Jin et al., 2015; Fudali-Czyż et al., 2016; Shang et al., 2017). Recent studies have also investigated the effect of cultural backgrounds on EEG responses to brain extension (Fudali-Czyż et al., 2016), compared EEG patterns between brand extension and new brand creation (Jin et al., 2015) or examined the logo effects on EEG responses to brand extension (Shang et al., 2017). However, all of these studies have focused only on goods-to-goods brand extension, that is, an extension of the product brand name into new goods [e.g., a new beverage, clothes, or an appliance of Coke (Ma et al., 2008)]. Considering that the service industry accounts for an ever-growing share in the global economy (Van Riel et al., 2001), it becomes increasingly important to investigate cognitive processes of consumers dealing with service-related brand extension.

However, not only was there no neuromarketing study on service-related brand extension, but also most marketing studies have focused on goods-to-goods brand extension. Only a few studies have so far examined the cognitive aspects of consumers' evaluation on service-to-service brand extension (Van Riel et al., 2001; Lei et al., 2004; Brown et al., 2011; Arslan and Altuna, 2012). For instance, Van Riel et al. (2001) suggested a complementarity to the original category as a major cue in evaluating service brand extension. Arslan and Altuna (2012) revealed that service extension is more favorable than goods extension for parent service brand. But, these studies relied on subjective evaluations through surveys, providing only partial information to comprehend consumers' cognitive evaluation processes on service-related brand extension.

The purpose of this study is, therefore, to conduct the first neuromarketing study to understand cognitive processes for the service-to-service brand extension strategy. To this end, we investigate underlying neural processes using EEG measurements along with the event-related potential (ERP) analysis. The previous neuromarketing studies on goods-to-goods brand extension have revealed that brand extension evaluation was related to several cognitive processes, including conflict monitoring between physical attributes and lexical contents reflected on the ERP component of N2 (N270) (Ma et al., 2007, 2010), and the categorization process reflected on the ERP component of P300 (Ma et al., 2008) and N400 (Wang et al., 2012). Furthermore, an additional study by Ma et al. (2014b) depicted the goods-to-goods brand extension evaluation as a two-stage categorization process expressed in P2 and N400 components. Recently, Fudali-Czyż et al. (2016) conducted a brand extension evaluation study with Indo-European language speakers and showed that N270, P300, and N400 components were responsive to incongruence between the original brand name and extended product name. These studies collectively suggest that some or all of these ERP components would also emerge during the evaluation of service-to-service brand extension.

One of the characteristics that distinguish service from goods offerings is heterogeneity, which refers to a difficulty to support consistent quality for individual consumers (Zeithaml et al., 1985; Iacobucci, 1998). This heterogeneity may lead individuals to recognize larger differences between the parent and extended service offerings compared to the extension of goods brand. Another distinguishable characteristic of the service offering, intangibility (Parasuraman et al., 1985), may make service extension more ambiguous to be systematically categorized than the goods extension. In these regards, we hypothesize that cognitive process engaged in evaluating service-to-service brand extension would not be identical to those in goods-to-goods extension, presumably showing different waveforms of the ERP components compared to those induced by goods-to-goods extension. Benchmarking against the ERP results from the previous goods-to-goods brand extension studies, the present study performs the experiment of service-to-service brand extension and compares experimental ERP results to those of goods-to-goods brand extension. In addition, due to the heterogeneity and intangibility of the service offering, the variation of individual attitudes to each service is generally greater than that to the goods. Consequently, it is challenging to prepare a stimulus pair of the parent brand and extended service representing either similar or dissimilar (i.e., typical or atypical) brand extension, which is different from the case of the previous goods-to-goods brand extension studies where similar or dissimilar brand extension exemplars could be more clearly created by experimenters (Ma et al., 2010; Wang et al., 2012). To overcome this issue, we propose a data-driven method to classify service extension stimulus pairs into similar versus dissimilar groups based on a "fit" level obtained from behavioral responses.

MATERIALS AND METHODS

Participants

A total of 37 participants (19 males, mean age of 22.1 ± 0.33 years old) with normal or corrected-to-normal vision and reportedly no any neurological disorders participated in this study. Smoking and drinking were prohibited within one day before the experiment. All participants provided informed written consent prior to participation according to the approval obtained from the Institutional Review Board of the Ulsan National Institute of Science and Technology (UNISTIRB-16-29-G).

Experimental Stimuli

Experimental stimuli were collected from previous service-to-service brand extension studies (Lei et al., 2004; Brown et al., 2011; Arslan and Altuna, 2012) and modified for Korean participants (**Table 1**). The set of parent service brand names (S1) consisted of eight service brands from four service categories: e-commerce, finance, airline, and accommodation (two brands per category). It was confirmed that all brands were familiar to participants. The set of extended service names (S2) comprised seven service names per category. Combining all the S1 and S2 data, we created a total of 56 stimulus pairs of S1-S2 service-to-service extension. Due to the aforementioned characteristics of the service offering, it was difficult to determine *a priori* whether each S1-S2 pair in this set was typical or atypical. Instead, we classified each pair based on a "fit" level that was calculated from the participants' responses obtained in the experiment.

Experimental Procedure

Participants were seated in a dim and electrically shielded room. Before the experiment, each participant was given a written instruction about the experiment. The experiment consisted of one training block followed by four test blocks, each containing 56 trials. In a single block, each of the 56 S1-S2 stimulus pairs was randomly presented to participants. All the visual stimuli were presented on a 27-inch monitor (QH2700-IPSMS, Achieva Korea, Incheon, South Korea) positioned at 60 cm distant from participants' eyes. The S1-S2 presentation paradigm with an explicit evaluation task (Ma et al., 2007, 2008; Jin et al., 2015; Fudali-Czyż et al., 2016; Shang et al., 2017) was employed in this study (**Figure 1A**). At the beginning of each trial, a fixation (i.e., white cross) appeared for 500 ms at the center of the black screen. Immediately after the fixation disappeared, one of the service brand names (S1) was presented, followed by the presentation of one of the extended service names (S2). Each stimulus was displayed for 1,000 ms with an inter-stimulus interval (*ISI*) of 500 ms. After the presentation of S2, participants were asked to evaluate whether the given brand extension was acceptable or not to themselves with a keyboard ("right arrow" key for acceptable and "left arrow" key for not acceptable). The next trial began 2,000 ms after participants responded. Participants were instructed to take a break long enough between the blocks.

After the experiment, participants took a memory test that was used to verify that they attended to the experiment. The memory test consisted of 30 stimulus pairs, including 11 brand extension pairs not used in the experiment. In the memory test, participants answered whether they had seen a given brand extension pair during the experiment. All participants showed a tolerable error rate under 33% (i.e., less than 10 wrong answers to 30 questions). Finally, participants filled in the survey form that consisted of the seven questions asked for each S1-S2 pair: (Q1) acceptance rate; (Q2) quality expectancy; (Q3) preference; (Q4) similarity between a typical service of S1 brand and S2 service; (Q5) acceptance rate of the brand extension strategy (i.e., attitude toward the marketing strategy); (Q6) attitude toward the S1 brand; and (Q7) own knowledge level regarding the S2 service (see Supplementary Material for the questions). Participant was asked to indicate how they agreed with each question with the 7-point Likert scale (1 – strongly disagree, 7 – strongly agree).

EEG Recordings

During the experiment, scalp EEG signals were recorded (band-pass filtering: 0.05-100 Hz, sampling rate: 500 Hz) using the 31-channel wet-electrode EEG recording system (actiCHamp, Brain products GmbH, Gilching, Germany) from the following electrode locations: FP1, FPz, FP2, F7, F3, Fz, F4, F8, FC9, FC5, FC1, FC2, FC6, FC10, T7, C3, Cz, C4, T8, CP5, CP1, CP2, CP6, P7, P3, Pz, P4, P8, O1, Oz, and O2 (in accordance with the International 10/20 system). We distributed electrodes over the wide range of scalp from prefrontal to occipital areas in a sagittal direction and symmetrically in the coronal direction, using the maximum number of EEG channels provided by the EEG apparatus. An additional electrode was applied to the left mastoid (TP9) as a ground. The EEG signals were on-line referenced to the right mastoid (TP10) (**Figure 1B**). Impedance of every electrode was set below 10 kΩ during the recordings.

Data Analysis

The behavioral data obtained in the experiment included affirmative responses during the experiment and responses to the seven questions after the experiment. The affirmative rate (AR) of each of the 56 pairs was calculated by averaging 4 binary acceptance responses. Note that among 37 participants, the data of a participant whose experiment was interrupted and 4 participants who did not response to survey correctly were excluded from the analysis. In addition, the data of 13 participants were additionally excluded from the EEG analysis due to following issues: (1) the EEG data of 4 participants were visually inspected as too much noisy despite the independent component analysis (ICA) method to reduce artifacts; and (2) the AR data of 9 participants failed to give the minimum number of trials for each fit group (the minimum of 12). Consequently, the EEG and behavioral data of a total of 19 participants were analyzed (9 males, mean age of 20.6 ± 0.48 years old).

TABLE 1 | Stimuli pairs lists.

Category (4)	E-commerce	Finance	Airline	Accommodation
S1: Service brand name (B1∼B8)	11st (*B1*)	Kookmin Bank (*B3*)	Korean Air (*B5*)	Lotte Hotel (*B7*)
	G-market (*B2*)	Shinhan Bank (*B4*)	Asiana Airline (*B6*)	Walkerhill Hotel (*B8*)
S2: Extension service name (ES1∼ES7)	TV home shopping channel	TV economy channel	Travel agency	Club
	Fashion magazine	Economy magazine	Travel information magazine	Catering service
	Travel agency	Education service	Simultaneous interpretation	Travel information magazine
	Insurance service	Legal counseling	Accommodation reservation	Travel agency
	Marketing consulting	Hospital	TV documentary channel	Legal counseling
	Newspaper	Simultaneous interpretation	Rent-a-car	Hospital
	Food delivery	Airline	Education	Finance

A total of 56 stimuli pairs were written as following examples: TV home shopping channel of 11st (B1-ES1), Simultaneous interpretation service of Shinhan Bank (B4-ES6), or Legal counseling of Walkerhill Hotel (B8-ES6).

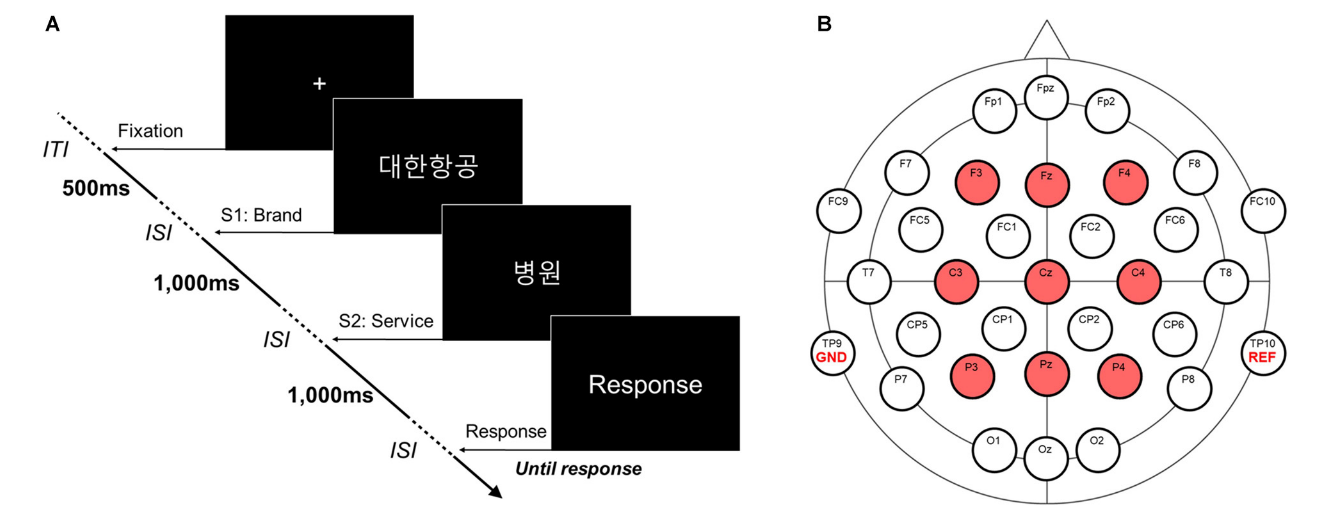

FIGURE 1 | An experimental task and an EEG montage. **(A)** An experimental task for evaluating service brand extension. A total of 56 S1-S2 pairs were presented consecutively in Korean [e.g., Hospital service (병원) of Korean airline (대한항공)]. There was no time limitation for response. Inter-trial interval (*ITI*) and inter-stimulus interval (*ISI*) were 2,000 and 500 ms, respectively. **(B)** EEG montage. A total of 32 EEG channels, including one reference channel (i.e., TP10) and one ground channel (i.e., TP9) were simultaneously measured. Nine channels (i.e., F3, Fz, F4, C3, Cz, C4, P3, Pz, and P4) were used to analyze ERPs.

To investigate behavioral responses of "fit" between S1 and S2 stimuli, each S1-S2 pair was assigned to a low-fit (AR = 0), mid-fit (AR = 0.25, 0.5, or 0.75), or high-fit (AR = 1) group depending on each participant's subjective AR response. Specifically, as individual participants were likely to evaluate the same S1-S2 pair differently, the grouping of the stimulus pairs was formed individually for each subject. **Figure 2** shows the mean and SE of AR across participants. In **Figure 2**, we also visualized the number of times each stimuli pair was assigned to each group via color-coding (i.e., The RGB value of each point represents the ratio of low-, mid-, and high-fit, respectively). **Figure 2** shows that the variance of AR increased for the S1-S2 pairs with moderate average near 0.5 and that some pairs were perceived to suit to a subset of participants but not to others (e.g., those in purple). This indicates that the perceived fit levels for certain brand extension substantially varied across individuals and thus supports our approach of individual grouping of stimuli. We also compared the reaction time (RT) and responses to seven questions between the three groups using a one-way repeated measure ANOVA with a Bonferroni's corrected *post hoc* paired *t*-test.

As a further analysis for behavioral data, to examine relationships between behavioral responses, a pairwise Pearson's correlation analysis was conducted between every combination of eight responses, creating an 8 × 8 symmetric correlation coefficient matrix per subject. To examine whether a correlation between a particular pair of responses was statistically different from a correlation between another pair, we conducted a pairwise comparison between every possible pair of the correlation coefficients using a paired *t*-test with Bonferroni's correction ($N = 19$). For this test, each correlation coefficient (r) was transformed to a z-value using the Fisher's z-transformation (Eq. 1), because the correlation coefficient was limited in the range of $(-1, 1)$ resulting in the violation of normality.

$$z = \frac{1}{2}\ln\left(\frac{1+r}{1-r}\right) \tag{1}$$

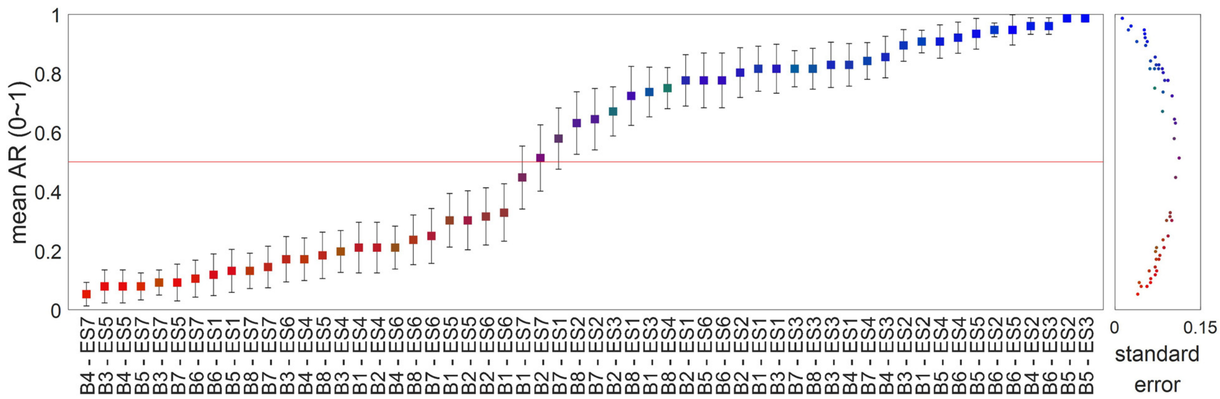

FIGURE 2 | The distribution of the affirmative rate (AR) for each stimulus pair of service-to-service extension. Each squared point shows the mean AR across participants in response to each pair of brand name (S1) and extended service (S2) stimuli (a total of 56 stimuli) (see the section "Data Analysis"). The black lines across the squares denote the SEM AR. These values of the SE are also illustrated in the right panel as dotted points. The RGB colors of the squares and dots represent the frequency that participants assigned a pair to each of the three fit groups: low- (red), mid- (green), and high-fit (blue).

The recorded EEG data were analyzed offline using the MATLAB software (version 2016a, MathWorks, Inc., MA, United States). Among the 31 channels, the following 9 channels were selected for the analysis to be comparable with the previous results (Ma et al., 2014b; Fudali-Czyż et al., 2016): F3, Fz, F4, C3, Cz, C4, P3, Pz, and P4. Although other fronto-central (FC9, FC5, FC1, FC2, FC6, and FC10) and centro-parietal (CP5, CP1, CP2, and CP6) channels were additionally analyzed in the previous studies, we did not include them in the analysis because our EEG system did not provide midline channels needed to compare the results. The EEG signals at each channel were band-pass filtered with 0.5 and 50 Hz cutoff frequencies using a FIR filter. Next, eye blink artifacts were removed using the ICA method. Then, EEG epochs were extracted from a 1,000-ms data segment (−200∼800 ms post-stimulus) time-locked to the onset of the second stimulus (S2) and corrected to each baseline (−200∼0 ms time-locked to the onset of S2). The EEG epochs from the trials of interest (e.g., the trials of S1-S2 pairs leading to a high-fit response) were averaged to obtain ERPs, excluding any trial with a peak-to-peak deflection exceeding $\pm$ 85 μV. Finally, the ERP waveforms were low-pass filtered using a Butterworth filter (30 Hz, third order zero-phase IIR filter).

To statistically assess the ERP components observed during the evaluation of service-to-service brand extension, 3 (Fit) $\times$ K (Channel) two-way repeated measures ANOVA tests were applied to the amplitudes of the observed ERP components. The number of channels, K, was determined depending on the observation of ERP components. In other words, if the tested ERP component was visually pronounced only in a subset of the nine channels, K was the number of those channels showing the tested ERP components. For *post hoc* tests on the main effect of the factor of fits, Bonferroni's corrected pairwise t-tests with the ERP component amplitude data were conducted between three fit levels (low-, mid-, and high-). For *post hoc* tests on the interaction effect of the two factors, one-way repeated measures ANOVA tests with the ERP component amplitude data for K channels were conducted. Greenhouse-Geisser correction was used when Mauchly's test showed that the sphericity assumption was violated (in this case, uncorrected degrees of freedom were reported as ε in addition to a corrected p-value). Bonferroni's correction was used for adjusting p-values for multiple comparisons.

RESULTS

Behavior Results

The ANOVA showed that reaction time (RT) was significantly different among the three fit groups ($F_{(2,36)} = 15.416$, $p < 0.001$) (**Figure 3A**). A Bonferroni's corrected multiple comparison *post hoc* test revealed that RT of the mid-fit group [mean (M) = 747.529 ms, SE = 99.186] was significantly slower than those of the high-fit (M = 513.841 ms, SE = 55.601, $t_{(18)} = 4.220$, $p < 0.001$) and the low-fit (M = 552.773, SE = 82.345, $t_{(18)} = 4.467$, $p < 0.001$) groups, while no significant difference was found in RT between the high-fit and low-fit groups ($t_{(18)} = 1.109$, $p = 0.282$). Repeated measures ANOVA for subjective responses to seven questions revealed significant differences among the three fit groups for every question ($ps < 0.05$) (**Figure 3B**). Bonferroni's corrected pairwise *post hoc* t-tests between the fit groups showed more positive subjective responses in the high-fit group than mid-fit group, and subsequently in the mid-fit group than low-fit group, for every question except for Q7 (i.e., prior knowledge about an extended service) in which no difference was found between the low- and mid-fit groups ($t_{(18)} = 1.431$, $p = 0.170$) (**Figure 3C**).

The pairwise Pearson's correlation coefficients between eight behavioral responses (seven responses to survey questions and one AR response during the task) were calculated and transformed to Fisher's z-values. The resulting 28 (${}_8C_2 = 28$) z-values were illustrated as nodes in **Figure 4**. The pairwise t-test for identifying differences between the z-values of a pair of nodes showed that the z-values associated with the seventh survey question (Q7: own knowledge level regarding the S2 service)

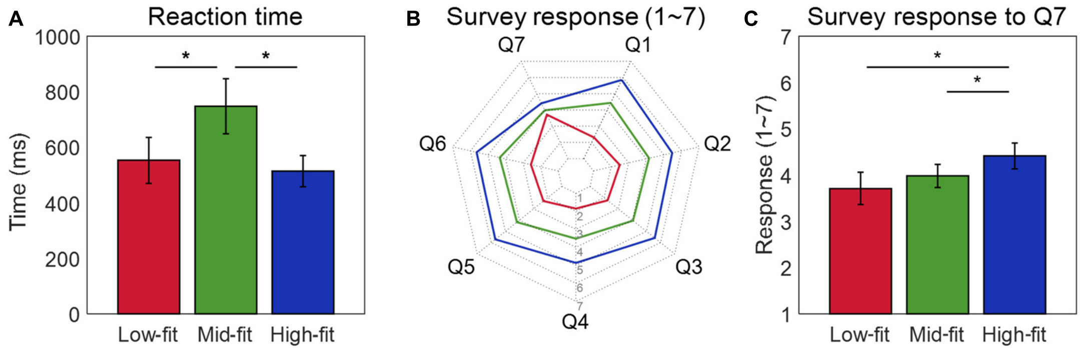

FIGURE 3 | Comparison of behavioral responses between three fit groups. **(A)** Group-wise reaction time of participants when evaluating whether a given brand extension was acceptable or not to themselves by pressing a keyboard. **(B)** Group-wise survey responses for each of seven questions. All pairwise *t*-tests for the six questions (Q1–Q6), except for Q7, showed significant difference between three groups. **(C)** Group-wise survey responses for Q7 regarding participants' background knowledge about extended service. *Indicates a significant difference between two fit groups ($p < 0.05$).

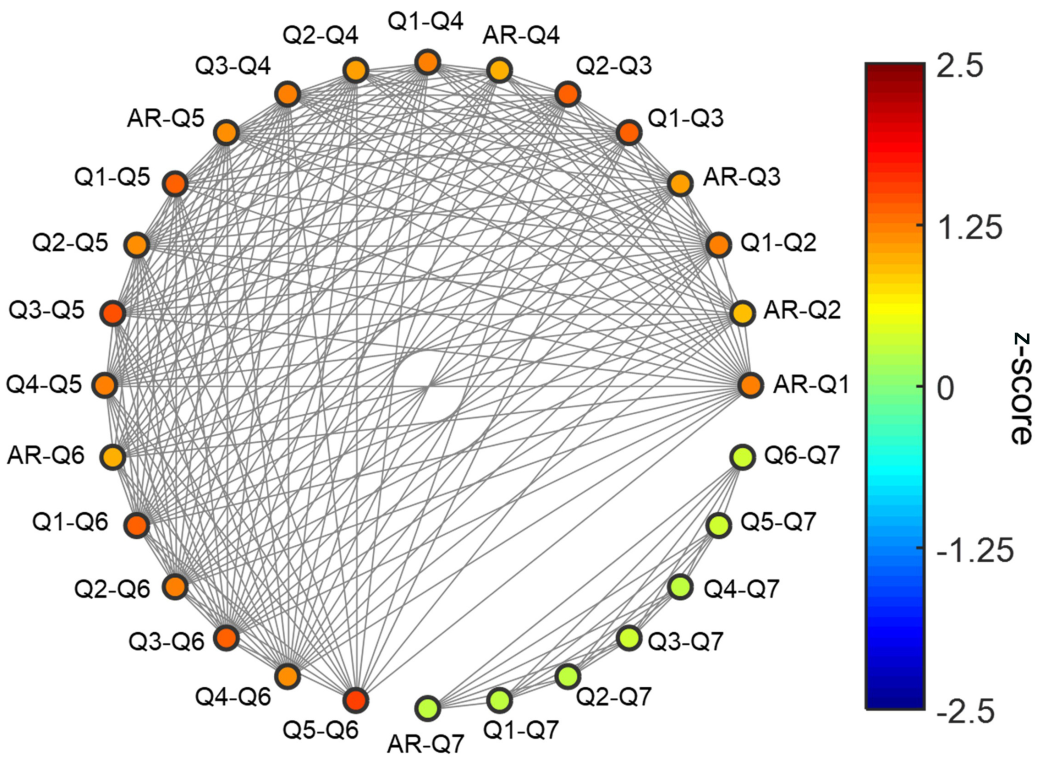

FIGURE 4 | A diagram of 28 correlation coefficients between eight questions. A total of 28 correlation coefficients of behavioral responses between every possible pair of eight questions (seven questions and the AR) were represented as the nodes (colored circles). Each node was color-coded using the *z*-score of the correlation coefficients. A pair of nodes was connected by gray lines if there were no significant differences between the correlation coefficients of the nodes (*z*-scores, $p < 0.05$).

were significantly lower than other *z*-values ($p < 0.05$). Note that there was no significant difference within the Q7-related *z*-values ($p > 0.05$), indicating that Q7 was not correlated with any other behavioral responses.

ERP Results

Although our experimental paradigm was identical to those in the previous goods-to-goods brand extension studies (Ma et al., 2007, 2008, 2014b; Fudali-Czyż et al., 2016; Shang et al., 2017), the ERP waveforms of our study exhibited differences from the previous ones. In our study, the ERPs showed that three positive or negative peaks—N2 (170∼230 ms), P3 (270∼330 ms), and N400 (370∼430 ms)—were prominent in every stimulus group (**Figure 5**). N2 and P3 were observed at all electrodes (F3, Fz, F4, C3, Cz, C4, P3, Pz, and P4) in the frontal, central, and parietal areas. N400 was observed at six electrodes (F3, Fz, F4, C3, Cz, and C4) in the frontal and central areas, but not in the parietal area.

As such, we further investigated the spatial patterns of these ERP components by constructing topographies of the ERP amplitudes for three different fit groups (i.e., high-, mid-, and low-fit stimuli) at 200, 300, and 400 ms after stimulus onset. The topographies at these three latencies showed that the low-fit stimuli elicited larger positive amplitudes at 300 ms as well as smaller negative amplitudes at 400 ms compared to other stimuli (**Figure 6**). At both 300 ms and 400 ms, the amplitudes tended to increase following the sagittal direction from anterior to posterior regions. The most salient spatial pattern was relatively smaller amplitudes at right frontocentral areas at both 300 and 400 ms.

To quantify these observations, the statistical tests (see the section "Data Analysis") on the amplitudes of each of the three components were conducted individually (**Figure 7**). For the N2 amplitude, two-way repeated measure ANOVA showed neither interaction nor any significant main effects of both factors (Fit and Channel) ($p > 0.05$).

For the P300 amplitude, two-way repeated measure ANOVA revealed a trend of main effect of "Fit" ($F_{(2,36)} = 2.472$, $p = 0.0986$) and a significant main effect of "Channel" ($F_{(8,144)} = 22.302$, $\varepsilon = 0.357$, $p < 0.001$). *Post hoc* tests on the main effect of "Fit" revealed that the P300 amplitude was significantly higher for the low-fit group ($M = 4.420$ μV, SE = 0.0205) than the high-fit ($M = 3.567$ μV, SE = 0.0186, $t_{(170)} = 4.776$, $p < 0.001$) or the mid-fit ($M = 3.579$ μV, SE = 0.0221, $t_{(170)} = 5.709$, $p < 0.001$) groups. The difference in the P300 amplitude between the high-fit and mid-fit groups was insignificant ($t_{(170)} = 0.0611$, $p = 0.951$). In addition, ANOVA showed a significant interaction effect between the "Fit" and "Channel" factors on the P300 amplitude ($F_{(16,288)} = 2.207$, $\varepsilon = 0.367$, $p = 0.049$). Further analyses on the interaction effect revealed significant effects of "Fit" only at F4 ($F_{(2,36)} = 4.937$, $p < 0.05$) and C4 ($F_{(2,36)} = 4.470$, $p < 0.05$) over the right hemisphere. The result also showed a trend of significant effects at the Fz ($F_{(2,36)} = 2.861$, $p = 0.0703$) and Cz ($F_{(2,36)} = 3.047$, $p = 0.06$) over the midline.

For the N400 amplitude, two-way repeated measure ANOVA showed a significant main effect of "Channel" ($F_{(5,90)} = 28.97$, $\varepsilon = 0.508$, $p < 0.001$) and a trend of main effect of "Fit" ($F_{(2,36)} = 2.475$, $p = 0.0983$). *Post hoc* tests on the main effect of "Fit" showed that the N400 amplitude was significantly more negative for the high-fit ($M = -0.252$ μV, SE = 0.0286, $t_{(113)} = 4.490$, $p < 0.001$) and the mid-fit ($M = -0.442$ μV, SE = 0.0347, $t_{(113)} = 4.266$, $p < 0.001$) groups than the low-fit group ($M = 0.688$ μV, SE = 0.0267). The difference of the N400 amplitude between the high-fit and mid-fit groups was insignificant ($t_{(113)} = 0.745$, $p = 0.458$). The test also showed a trend of an interaction effect between the "Fit" and "Channel" ($F_{(10,180)} = 1.954$, $\varepsilon = 0.494$, $p = 0.0942$). Further analyses on the interaction effect revealed significant effects of "Fit" only at Cz ($F_{(2,36)} = 3.373$, $p < 0.05$). The result also showed a trend

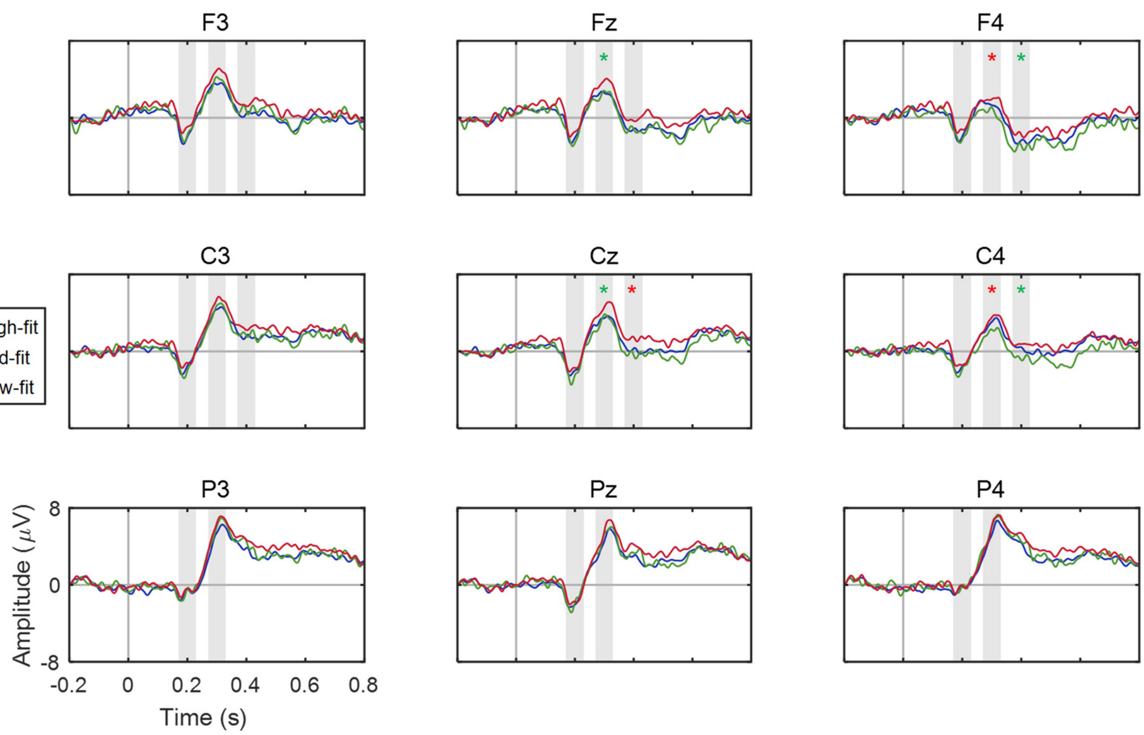

FIGURE 5 | ERP waveforms of nine EEG channel locations. The mean ERP waveforms across participants were obtained for each fit group and each channel. The vertical bars at 0 s denote the onset of stimulus (extended service; S2). Red and green asterisk marks (*) indicate a significant difference ($p < 0.05$) and a trend of difference ($p < 0.10$) between low and high fit groups, respectively. The shaded areas represent the ERP components observed in this study.

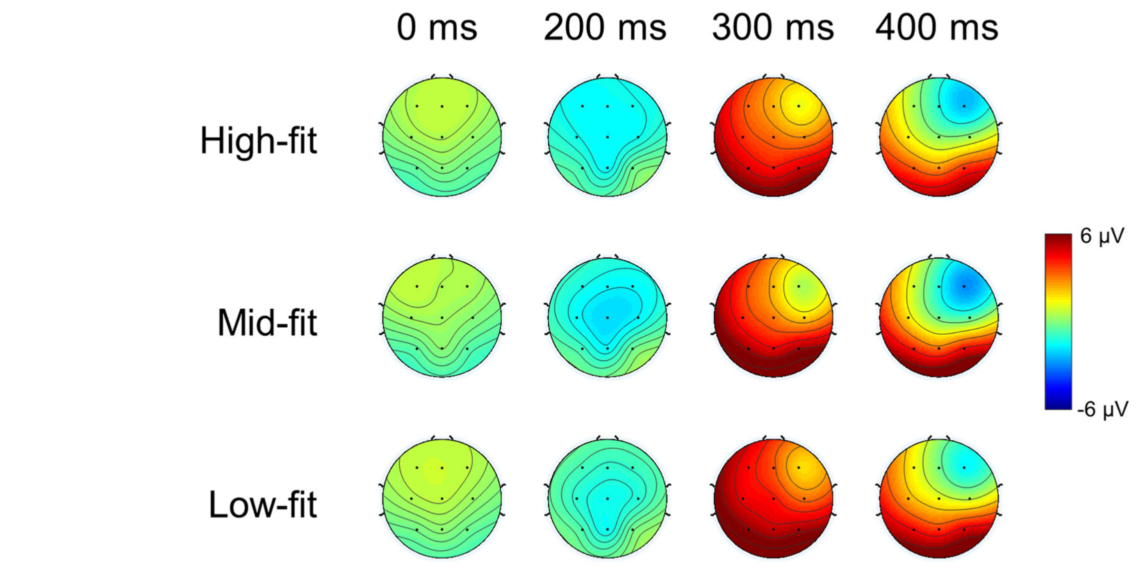

FIGURE 6 | ERP topography. The topographies of the ERP amplitudes for three different fit groups (i.e., high-, mid-, and low-fit) at 0, 200, 300, and 400 ms after stimulus (extended service; S2) onset. The color level denotes the mean ERP amplitude across participants. The black dots represent the EEG channels from which ERPs were analyzed in this study: F3, Fz, F4, C3, Cz, C4, P3, Pz, and P4.

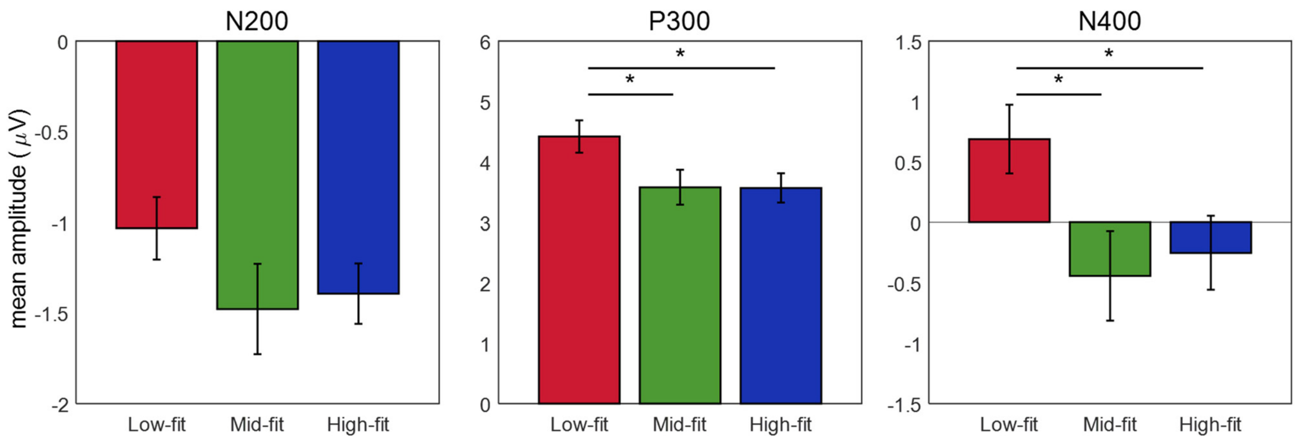

FIGURE 7 | Comparison of the ERP component amplitudes among the fit groups. The mean amplitudes of three ERP components across participants and channels, including N200, P300, and N400, were calculated for each fit group (low-, mid-, and high-fit). *Indicates a significant difference between two fit groups ($p < 0.05$).

of significant effects at F4 ($F_{(2,36)} = 3.0702$, $p = 0.0587$) and C4 ($F_{(2,36)} = 3.149$, $p = 0.0549$) over the right hemisphere.

DISCUSSION

Previous studies on neural correlates of the brand extension evaluation using ERP methods considered only goods-to-goods brand extension. On the contrary, this ERP study investigated neural activities during service-to-service brand extension.

Except for the difference of the type of extension, namely service versus goods, a crucial difference between the current study and the previous brand extension studies was a way of grouping stimuli. In the previous studies (Ma et al., 2007, 2008, 2010, 2014a,b; Wang et al., 2012; Jin et al., 2015; Fudali-Czyż et al., 2016), stimulus pairs were grouped into high-fit, mid-fit, and low-fit sets manually by experimenters based on the product category each goods belongs to (e.g., beverage versus non-beverage, snacks, clothing, or household appliances). It reflects an implicit assumption that there is little across-subject variation in perceived fit levels for a given goods-to-goods pair. However, such an assumption may not work well with service offering because it is too ambiguous to categorize services in accordance with a common sense and the experience of the quality of services can considerably vary over consumers, having each consumer mentalizing different concepts of the same service. Hence, for a service-to-service brand extension study, stimulus pairs may need to be grouped based on subjectively felt fit levels. In our study, stimulus pairs were divided into three groups (i.e., low-, mid-, and high-fit) according to participants' AR responses during the brand extension evaluation task. Our results showed large variance across participants in the ARs for ambiguous stimuli, supporting the idea that stimulus grouping should be conducted based on subjective responses (**Figure 2**).

Some examples of service-to-service extension showed interesting grouping results. For instance, the education service extended off two airline service brands (i.e., Korean Air and Asiana Airline) was categorized as high-fit stimuli by 18 and 15 participants (out of 19), respectively. Also, 14 participants evaluated interpretation service extended off two financial service brands (i.e., Kookmin Bank and Shinhan Bank) as high-fit brand extension. In most cases, the extension of two brands belonging to the same service category (e.g., Airline) to a certain service was evaluated as a similar fit level. Exceptionally, participants' evaluations on the brand extension of two brands of the hotel category were slightly different. These results might indicate that consumers largely consider the characteristics of service category first and then fine-tune their evaluation based on the characteristics of individual brands on occasion.

The result of RT in our study was similar to that of the previous study carried by Ma et al. (2007), which compared beverage brand extension to four product categories (i.e., beverage, snack, clothing, and household appliances). In their study, RT was the fastest for beverage-beverage (high-fit), the slowest for beverage-snack (low-fit) and in between for other cases (mid-fit). It indicates that our S1-S2 grouping based on participants' responses could provide a valid means to estimate a fit level during service-to-service brand extension evaluation. Yet, no difference in RT was found between the low-fit and high-fit stimuli in our data, dissimilar to the previous results about goods-to-goods brand extension where fit levels perceived by consumers could be inferred from the RT data (Ma et al., 2007, 2008; Jin et al., 2015). In the case of service-to-service brand extension, however, we found that RT for both high-fit and low-fit stimuli was indistinguishable, which may imply that more than just RT data are needed to explore why a consumer evaluated various cases of brand extension with different fit levels. This leads us into exploring neural activity to find distinguishable responses between high-fit and low-fit stimuli.

Our behavioral data analysis showed that the knowledge level of extended services was not correlated with other behavioral responses associated with brand extension evaluation such as AR, expected quality, preference, and brand attitude. In the brand extension evaluation task of this study, the brand name was a unique cue with which participants evaluated brand extension. Therefore, our results indicate that behavioral responses to an unfamiliar service of a familiar brand were primarily affected by participants' experiences to that brand name (S1) even though they did not know well about extended service (S2). It may underscore a key role of brand images in brand extension evaluation.

The ERP components resulted from our study can be compared with the previous results from the goods-to-goods brand extension evaluation. Compared to the goods-to-goods brand extension study by Ma et al. (2014b) where P2 and N400 were reportedly observed, our ERP analysis results showed only N400. On the other hand, the result of another goods-to-goods brand extension study by Fudali-Czyż et al. (2016) exhibited N2 and P300 similar to our results. A primary difference between these two goods-to-goods extension studies was the way participants responded during the experimental task. In the study by Ma et al. (2014b), participants did not have to behaviorally respond, whereas in the study by Fudali-Czyż et al. (2016), participants explicitly responded whether each brand extension pair was affirmative or not. Wang et al. (2012) suggested that P300 could reflect a combined effect of categorization and explicit evaluation during the brand extension evaluation task as they did not observe P300 in their implicit task. Since our task also required explicit responses by participants and elicited the ERP components similar to those by Fudali-Czyż et al. (2016), our results may support the suggestion of Wang et al. (2012) and Fudali-Czyż et al. (2016) that explicit evaluation of brand extension may involve categorization manifested by the ERP components of N2 (N270), P300, and N400. Our results of the pronounced P300 with the maximum at parietal areas and N400 with the maximum at frontal areas were also consistent with to the previous results (Wang et al., 2012; Ma et al., 2014b).

However, our results differed from those by Fudali-Czyż et al. (2016) or Ma et al. (2008) with respect to the P300 amplitude. The P300 amplitude was higher for the low-fit (incongruent) group than others in our study whereas it was higher for the high-fit (congruent) group in the previous studies. In the previous studies, participants responded to each stimulus pair in terms of approvability (i.e., "This brand extension fits well enough to sound approvable to me."). However, in our study, participants were likely to evaluate each stimulus pair in terms of improbability (i.e., "This brand extension is highly improbable"). As mentioned above, consumers may feel more difficult in categorizing service than goods. Therefore, it might be challenging to them to divide stimulus pairs based on approvability. Instead, they might evaluate how improbable a pair was, classifying the pair into the low-fit (improbable) group versus others. Our ERP result supports this conjecture regarding a difference of evaluation processes between goods-to-goods and service-to-service brand extension. Previous studies about P300 amplitude showed that P300 amplitude is relevant to detection of improbable target stimuli (Duncan-Johnson and Donchin, 1982; Stuss et al., 1986; Azizian et al., 2006). Hence, a higher P300 amplitude for the low-fit group in our results might indicates the detection of an improbable (low-fit) stimulus pair.

Our results of N400 might represent the later cognitive process of brand extension evaluation. N400 was considered to reflect a late categorization process according to the integrality category concept between S1 and S2 (Ma et al., 2014b). In the previous study (Ma et al., 2008), N400 was predominantly evoked by the conflict condition (i.e., non-beverage products of beverage brand) and noted that it could be an endogenous index for the evaluation of unfitted brand extension. Another study by

Wang et al. (2012) reported stronger N400 at frontal areas and suggested that it reflected the integration and conceptual analysis process of the extended goods into the parent brand. In the present study, we observed that the N400 amplitude for the low-fit stimulus group was greater than zero with a negative peak (**Figure 7**). We speculated that this weak N400 component occurred as participants filtered out the low-fit stimulus pairs in terms of improbability (reflected by strong P300), skipping subsequent integration and categorization process represented by N400. On the contrary, for the mid-fit and high-fit stimulus pairs, participants might execute the late integration and categorization process to evaluate service-to-service brand extension more precisely. Therefore, N400 amplitude for mid-fit stimuli was more negative than high fit stimuli, showing more incongruence.

In our ERP data, N400 appeared predominantly at frontal channels, showing more negative amplitudes over right frontal areas (**Figure 6**). The study by Wang et al. (2012) reported stronger N400 at frontal areas and suggested that it reflected the integration and conceptual analysis process of the extended goods into the parent brand. Similarly, the observation of frontal N400 in our study may reflect the integration of the extended service with the parent brand. In addition, Stringaris et al. (2006) suggested that the neural activation in the right frontal cortex indicate the attempt to establish a semantic relationship between successive items. Therefore, our results demonstrated more negative N400 amplitudes for high-fit and mid-fit stimuli than for low-fit stimuli, indicating that the establishment of a semantic relationship of brand and service might be facilitated for the stimuli with higher fit levels. Taking into consideration the implication of P300 for the detection of improbable low-fit stimuli, we speculate that there may be a "threshold" to detect low-fit stimuli based on improbability and then evaluate the rest stimuli through a process of integrating and establishing the semantic relationship between parent brand and extended service.

Ma et al. (2014b) explained about goods-to-goods brand extension as the two-stage cognitive process; consumers initially categorize a stimuli pair according to physical similarity followed by an analytic categorization process. However, our results may suggest that consumers are likely to evaluate service-to-service brand extension with a different categorization process. An *anterior* N2 component was observed at frontal and central areas in the present study, but no significant difference in the N2 amplitude was found between different fit levels. Previous studies revealed that *anterior* N2 is elicited in the sequential matching task to discriminate whether the physical attributes (i.e., color or shape) are equal between sequentially presented stimuli (Wang et al., 2003, 2004; Folstein and Van Petten, 2008; Luck, 2014). Therefore, no difference in *anterior* N2 amplitude between different fit levels in our study may indicate that consumers did not evaluate physical aspects of S1 and S2, because of the intangibility of service offering (Iacobucci, 1998).

There are some limitations in our study. First, the number of mid-fit stimuli turned out to be relatively small compared to other stimulus groups. Even with the exclusion of some participants' data by setting the minimum number of mid-fit stimuli, we could not balance the number of mid-fit stimuli with those of other groups. It may be due to that it was more natural to categorize service offering as binary classes (i.e., low or hard-fit). Second, categorization of the fit levels of service-to-service brand extension may be more complex than simple three levels of high-, mid-, and low-fit groups. Perhaps, a simple evaluation of brand extension with a single "fit" parameter might not be suitable for service-to-service extension, requiring more sophisticated measures. Lastly, we did not collect more subjective evaluation data by survey, which might be useful for the interpretation of how participants evaluated brand extension. For instance, we could perform an in-depth interview or a review session with the think-aloud protocol.

To resolve these problems, advanced stimuli grouping methods should be developed. To our knowledge, little is known about the fit level of service brand extension. Because stimuli grouping method is a basic step for service-to-service brand extension, it will remain crucial for the follow-up studies. Additionally, we compared our results with previous studies where Chinese (Ma et al., 2007, 2008, 2010, 2014a,b; Wang et al., 2012; Shang et al., 2017) or Indo-European language speakers (Fudali-Czyż et al., 2016) participated in. Previous studies reported that a cultural difference could affect favorability in evaluating brand extension (Monga and John, 2007). Chinese, Korean, and Indo-European people have different characters, languages, and cultures. The difference between cognitive processes between previous studies and present study could be affected by those differences. Therefore, further studies about either service-to-service brand extension evaluation of participants in different cultural backgrounds or goods-to-goods brand extension evaluation of Korean participants will enhance understanding of cognitive process in evaluating brand extension.

Despite above limitations, our findings suggest that EEG analysis show important information that we cannot know only with behavioral data (i.e., reaction time) analysis. The reaction time analysis revealed that participants' responses were significantly slow to mid-fit stimuli groups. However, low- and high-fit stimuli groups could not be distinguished only with reaction time data. In contrast, EEG result could distinguish those stimuli, suggesting two-stage cognitive process that first detecting and dropping low-fit stimuli based on improbability and second evaluating fit level based on incongruence. Therefore, a novel marketing tool to expect fit level of pre-formed brand extension before launching it using EEG analysis could be used for brand marketers. In addition, the present study suggested endogenous cognitive process in evaluating brand extension. For example, lower N400 amplitude and high P300 amplitude in low-fit stimuli indicate low integration and high improbability between parent brand and extended service, respectively. This result indicates that neuromarketing could help marketers, by providing objective and effective information about consumer decision making, in forming a marketing strategy as well as in evaluating pre-formed marketing strategy.

CONCLUSION

The present study investigated neural responses during consumers' evaluation of service-to-service brand extension. The analysis of ERPs revealed three components: N2, P300, and N400, which were different from those of the previous goods-to-goods brand extension studies. Based on behavioral responses regarding the fit level of parent brand and extended service, we divided the stimuli into three groups (low-, mid-, and high-fit groups) and compared each component between the groups. As a result, N2 did not show any significant difference between the fit groups, implying that different fit levels did not influence a basic perceptual process. P300 showed higher amplitudes for the low-fit group than others, indicating that participants might first sort out discrepant brand extension and then evaluated more congruent extension only. N400 showed more negative amplitudes for the mid- and high-fit groups, indicating facilitated semantic integration of extended service with parent brand for these groups. These neural responses suggest that the evaluation of service-to-service brand extension may involve different cognitive processes from those in the evaluation of goods-to-goods brand extension, and that different marketing strategies may be deployed for different types of brand extension.

AUTHOR CONTRIBUTIONS

TY participated in all aspects of the work, designed and conducted the experiment, analyzed the data, and wrote the manuscript. SL and ES conducted the experiment. S-PK oversaw the study and managed every part of research. All authors read and approved the final manuscript.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fnhum.2018.00044/full#supplementary-material

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Using Support Vector Machine on EEG for Advertisement Impact Assessment

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The advertising industry depends on an effective assessment of the impact of advertising as a key performance metric for their products. However, current assessment methods have relied on either indirect inference from observing changes in consumer behavior after the launch of an advertising campaign, which has long cycle times and requires an ad campaign to have already have been launched (often meaning costs having been sunk). Or through surveys or focus groups, which have a potential for experimental biases, peer pressure, and other psychological and sociological phenomena that can reduce the effectiveness of the study. In this paper, we investigate a new approach to assess the impact of advertisement by utilizing low-cost EEG headbands to record and assess the measurable impact of advertising on the brain. Our evaluation shows the desired performance of our method based on user experiment with 30 recruited subjects after watching 220 different advertisements. We believe the proposed SVM method can be further developed to a general and scalable methodology that can enable advertising agencies to assess impact rapidly, quantitatively, and without bias.

Keywords: EEG, SVM, advertisement impact assessment, neuromarketing, machine learning

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1. INTRODUCTION

Advertising plays a critical role in marketing. Every year, companies allocate a significant proportion of marketing budget to attempt to quantify the impact of their advertising, particularly video advertising on TV and on the web which receives wide viewership (Brady, 2014; Bradley, 2015). However, current methodologies, including both direct observation (questionnaires and focus groups prior to starting of the advertising campaign), and indirect (trends in sales or consumer interest during and after a campaign), tend to have practical or experimental challenges that reduce the effectiveness of the assessment (Goldberg, 1990; Ducoffe, 1996; Elliott and Speck, 1998; Lewis and Reiley, 2009; Ostrovsky and Schwarz, 2011).

Direct observation methods include questionnaires, and focus groups, where yet to be released advertisements (or multiple versions of an advertisement) are shown to a select group of viewers selected to be representative of the advertisement's intended audience. The viewers answer questions and provide feedback during a survey or engage in discussion with the organizers; then the results or discussion are analyzed by the advertising team to try to assess how well the advertisement fulfils the criteria of their campaign (Gaines et al., 2007).

However, direct approach methods are subject to the same kinds of challenges as other experimental psychology approaches: experimental biases are introduced due to the experimental environment (typically an office room with multiple participants) being different to how a viewer would normally view the advert (often in the comfort of one's own home), leading to a different state of mind of the viewer. There is a tendency for respondents to feel obliged to give more favorable reviews under experimental conditions of being under observation than they would typically do. The way the experiment is carried out in groups can also result in peer-pressure and group-dynamics altering the responses of individuals, leading to participants reporting attitudes or preferences that may not truly represent their own when they are in private (De Pelsmacker et al., 2002; Maison et al., 2004; Shen and Li, 2009). The analysis of survey feedback or discussion too can introduce experimenter-bias where the opinions of the experimenters impact the evaluation of the results; and the size and cost of conducting the study and analyzing the results is often cost-prohibitive past certain scales (and when considering TV advertising for national release, the size of these focus studies are often a tiny proportion of eventual viewership, resulting in uncertainty of the statistical relevance of the results).

Indirect observation methods of assessing advertising impact involve inferring advertising impact based on the result of an advertising campaign (Sharma et al., 2011). These methods avoid the inaccuracies imposed by artificial experimental conditions of direct observation methods but suffer from their own challenges. By looking only at the results and effects of the advertisement campaign, and because it is only possible to look at aggregated effects (such as the impact on sales or customer interest in a product), it is often difficult to identify if, why, and how a particular aspect of the advertisement causes an impact. Furthermore due to the life-cycle of an advertising campaign, it is only possible to infer impact during or after the launch of an advertising campaign, meaning in many cases, much or all of the cost of the campaign having been sunk, limiting adaptability in the event of lackluster response to the campaign (Kanetkar et al., 1992; Grewal et al., 1998; Sundar and Kalyanaraman, 2004).

In recent decades, research in neuroscience has brought new understanding and tools that can change how the impact of advertising can be assessed and has formed the new field of neuromarketing, in which recent neuroscience and experimental psychology tools and understanding are being applied to marketing. One key hypothesis in neuromarketing is that a consumers decisions can be driven more by emotion than by a careful comparison of product benefits or differentiators. Therefore, measuring an advertisement's emotional impact on an individual could correlate well with the impact of the advertisement.

In neuromarketing-based advertisement impact assessment, biometrics are gathered from individuals participation in the study, and these biometrics are used to assess impact, rather than voluntarily self-reported information from surveys or discussion. The recorded data includes biometrics such as eye-tracking, facial coding, Galvanic skin response and electrodermal activity, and EEG. EEG is a noninvasive electrophysiological recording of brain activity, using electrodes placed along the scalp. EEG has multiple advantages over other methods of measuring brain activity in that it has a high temporal resolution, is non-invasive, quick to instrument and tolerant to subject movement, and low cost with the use of single electrode equipment. In 2010, Murugappan found in a study of human-computer interaction, a correlation between a user's emotion and EEG, providing useful information in understanding a user's reaction to advertisements (Murugappan et al., 2010). Therefore, an increasing amount of research into neuromarketing has turned to EEG as a key sensor in measuring emotion. Lucchiari and Pravettoni observed that EEG signals with a frequency of 16–31 Hz (i.e., Beta wave) could be modulated by the experience of pleasure when a consumer was presented with a favorite brand (Lucchiari and Pravettoni, 2012). In 2016, Wang, Chang and Chuang found that a narratives structure in video commercials induced higher EEG signals with a frequency band of 4–7 Hz (i.e., higher Theta) power of the left frontal region resulting in higher preference for branded products (Wang et al., 2016).

In psychology research, a person's emotion can be quantified through self-reported measures such as liking (valence) and excitability (awaken) (Poels and Dewitte, 2006; Smit et al., 2006). Questionnaires can be used to gather this type of information. According to the AIDA model, four quantified metrics are used to characterize the experience for a consumer watching an advertisement: attention, interest, desire, and action (Strong, 1925).

In the literature, Support Vector Machine has been widely used on EEG data; research on EEG based emotion recognition using frequency domain features and Support Vector Machine (SVM) was done by Wang et al. (2011)Research on EEG-based emotion recognition in music listening using Support Vector Machine(SVM) was done by Lin et al. (2009) Though other regression in binary results can also be used to build this model, in the literature, Support Vector Machine is the most widely used method in this field. Also, Support Vector Machine is suitable because of the sparse dataset the experiment uses. The technique used will build a prediction model based on several different brainwaves, which include frequency band less than 4Hz (i.e. Delta), frequency band between 4 and 7 Hz (i.e., Theta), frequency band 8–15 Hz (i.e., Alpha), frequency band 16–31 Hz (i.e., Beta) and frequency bigger than 32Hz (i.e., Gamma).

In this paper, we test the hypothesis that it is possible to use low-cost EEG equipment to collect brainwaves of subjects viewing advertisement, and to apply the latest methods from neuromarketing, and machine learning as a more accurate method of assessing advertisement impact and the likelihood of a person purchasing the advertised product than the current state-of-the-art.

2. METHODOLOGY

This section of the paper will describe the method used to collect data from a single-electrode wearable EEG device, self-reported measures for the impact of an advertisement, and train a predictive model against the data using SVM (Poels and Dewitte, 2006; Smit et al., 2006; Chen et al., 2014).

2.1. Data Collection

In the experiment, thirty right-handed male participants aged 20–35 from the University participated in this experiment as paid volunteers. Thirty participants were in the experiment, each of them is given 4–5 advertisements, to create a sample size of 450, big enough to carry out statistical analysis. The experiment was carried in China, and the participants are bi-lingual in Chinese and English speaker. The participants had normal or corrected vision without any histories of neurological/mental diseases. The purpose of choosing bi-lingual participants is to avoid language-barrier caused by the advertisement's language content being in Chinese or English. We selected male participants to avoid biases from gender-specificity of the advertised products. Many products are specifically targeted at a particular gender, for example, male clothing and female clothing are targeted differently; as are hair and cosmetic products. We constructed a database of 220 TV advertisements from four gender-neutral or male-targeted products: cars (55 ads), digital products (55 ads), clothing (55 ads) and food (55 ads), which were randomly selected from Youku.com (one of the largest online media websites). Each advertisement was 15–20 s in length. The video resolution and audio volume of each video were normalised to the same level using professional video and audio editing software. In each test, 4–5 advertisements were randomly selected from the 220 TV advertisements database. The shortcomings and future research because of this design will be discussed in section 4.

Before the experiment, the volunteers received detailed instructions on all the tasks they would perform. Each participant was fitted with a single-electrode EEG headset by an experimenter, was seated comfortably in a lab room at 1.20 meters from a 19-inch PC monitor, and shown five advertisements randomly selected from every genre for a total of 20 advertisements. An E-prime system was used to control the presentation of the stimuli.

The experiment consisted of 4 blocks, each containing 20 trials. During every trial, the volunteers were presented with the advertising for about 15–20 s. The advertisement was followed by an evaluation questionnaire, including the willingness of the participant to purchase the advertised product (yes or no), and liking the advertisement (7-point Like scale).

Each volunteer performed two practice trials before the start of the formal experiment. The frontal EEG was recorded with the single-channel dry electrode-device and system (NeuroCAR1.0, Neuromanagement Lab, Zhejiang University, China). The integrated chip of the device was the ThinkGear (NeuroSky, Wuxi, China). The sampling rate of the device for gathering EEG signals was 512 HZ and the data saved into a computer. Four trials data were rejected due to voltage abnormality, and in total, 450 sets of brainwave data were used in our study.

2.2. Questionnaire Collection

The participants were asked to fill out a questionnaire with 22 questions asking about different aspects (objective and subjective) of the advertisement, or their experience. The questionnaire is listed in **Table 1**. The questionnaires are chosen to record different aspects of the advertising can impact the viewer's response to the advertising, which may indicate the likelihood of the viewer wanting to purchase the product. The aspects are chosen from several studies in the literature that each focus on one of two aspects of an advertisement's impact. M. Vaismoradi, Kimberly, and Klaus show that the audio and visual fidelity of the advertisement (Y2 and Y15 of the questionnaire) had an impact (Vaismoradi et al., 2013). The content impact are covered by questions Y1, Y5, and Y14. The brand quality is covered in (Y6, Y7, and Y8). The overall feeling of the advertisement (Y3 and Y4) was found to make an impact on a customer's decision to purchase or not (Dahlén, 2002; Niazi et al., 2012). The conscious decision reported by customers on whether they would make the purchase or not (Y9 and Y10). Padgett and Douglas Allen showed that advertising memorability also plays a role in purchase power (Y11 and Y12). (Padgett and Allen, 1997) Other impacts include: Celebrity endorsement (Y18) (Bocheer and Nanjegowda, 2013; Srikanth et al., 2013); the feature of children or cartoons (Y20 and Y21) (Blatt et al., 1972; Fischer et al., 1991); the language (Y13) (Noriega and Blair, 2008); the narrative style and story-telling (Y16, Y17, Y22) (McQuarrie, 2002; Phillips and McQuarrie, 2002); and sexual-appeal (Y19) is widely established to have an impact on advertisement (Severn et al., 1990; Weller et al., 2015).

TABLE 1 | The output dataset list.

	Output feature
$Y_1(1-7)$	Content Quality
$Y_2(1-7)$	Image Quality
$Y_3(1-7)$	Excitement
$Y_4(1-7)$	Attractiveness
$Y_5(1-7)$	Easiness for understanding
$Y_6(1-7)$	Clearness of the brand
$Y_7(1-7)$	Brand awareness
$Y_8(1-7)$	Familiarness of the brand
$Y_9(1-7)$	Willingness to buy
$Y_{10}(1-7)$	Intention to further learn the product
$Y_{11}(1-7)$	likeliness of memorize the advertisement content the next day morning
$Y_{12}(0/1)$	If the brand of the product can be memorized the next day
$Y_{13}(0/1)$	Chinese language or not
$Y_{14}(0/1)$	If it is moving
$Y_{15}(0/1)$	If it has significant vision and sound impact
$Y_{16}(0/1)$	If it is interesting
$Y_{17}(0/1)$	If it surprises you
$Y_{18}(0/1)$	Whether it has celebrities
$Y_{19}(0/1)$	If it is sexy
$Y_{20}(0/1)$	If it has children
$Y_{21}(0/1)$	If it has cartoon
$Y_{22}(0/1)$	If it is a story telling ads

Eleven of the questions had binary answers of 0 or 1; another eleven were ranked answers from 1 to 7. The questions are listed in each column as output data (see **Table 1**).

2.3. Modeling

Raw EEG data is first augmented into frequency domain EEG signal before creating a larger dataset necessary for analysis. In this paper, the frequency domain EEG signal is listed in **Table 2**. Further details of input data X is listed in section 2.3.1

TABLE 2 | The EEG band dataset list.

	Input feature	Meaning
X_1	Time Stamp	A sequence of numbers indicate the time index of raw signal
X_2	Signal Quality	Value ranges from 0 to 255
X_3	Raw	Voltage
X_4	Attention	Intensity of a user's level of mental focus/attention, value ranges from 0 to 100
X_5	Meditation	Level of a user's mental calmness/relaxation, value ranges from 0 to 100
X_6	Delta	>4 Hz
X_7	Theta	≥4 Hz and <8 Hz
X_8	Low Alpha	7.5–9 Hz
X_9	High Alpha	9.5–12.5 Hz
X_{10}	Low Beta	12–15 Hz
X_{11}	High Beta	15–18 Hz
X_{12}	Low Gamma	30–80 Hz
X_{13}	High Gamma	>80 Hz

The output data is labeled as Y. Each row of output data Y has 22 dimensions, and each dimension represents a feature, and all features are independent. $Y_{450\times22}$ can be written as $Y_{450\times22} = [Y_1, Y_2, ..., Y_{22}]$ where Y_i represents each column vector of Y, and $i = 1, 2, ..., 22$, see **Table 1**.

The purpose of this research is to use SVM to train a machine learning model that can find the map f, where $Y = f(X)$, the reason to use Support Vector Machine (SVM) is explained in section 2.3.4. Once found, any new input EEG signals can be translated into a prediction of an advertisement's impact on a consumer, and their likelihood of either a positive impression or willingness to buy the product.

Due to the format of the raw EEG signal data, data extraction is applied to amend the input data into the applicable format. Feature selection is conducted on input data, and label selection is conducted on output data. Among the thirty participants, data corresponding to twenty nine participants are used as in sample data. The sample workflow of this research is shown in **Figure 1**. 10% of the sample data is then separated as a testing dataset, with the remaining 90% used for training dataset. Bootstrapping is used to bootstrap the training dataset. The data corresponding to the remaining participant is used as out of sample test. The out of sample test is carried out by selecting each last person in the thirty participants and then averaged the thirty out of sample as judgment.

Support Vector Machine is applied as the machine learning method to predict the label given output data. Cross-validation and learning curve is eventually used to check over-fitting/under-fitting. We will elaborate each component in the workflow in the following sections.

2.3.1. Feature Extraction

Raw EEG signal is a voltage over time signal. Hence, a crucial process is needed to break the raw EEG signal into constituent frequencies (High alpha/beta/gamma/delta waves), etc. It is crucial because the majority of the informational content in EEG signals are in the frequency domain, so breaking up the signal into constituent frequencies is most appropriate to apply SVM to classify EEG frequency domain data. Besides, according to the research that has been done by Dong et al. (2017), frequency data is better for feature extraction than the raw time domain data. Feature extraction, specifically Fast Fourier transform (FFT) is used to transform the raw EEG signal from time domain into frequencies domain (Heideman et al., 1985; Van Loan, 1992; Pritchard et al., 1994). We computed the EEG frequency band power using traditional EEG frequency band definitions (Delta: 1–3 Hz; theta: 4 Hz, alpha I: 89Hz, alpha II: 1,012 Hz, beta I: 1,317 Hz, beta II: 1,830 Hz, gamma I: 3,140 Hz, gamma II: 4,150 Hz), and these are time signals for each frequency band. Also, because the band EEG signal is collected from the four different product types, and with duration of each advertisement being different, data is also needed to be normalized. Timestamps are used to represent the duration, and advertisement lengths are normalized by cutting advertisements to the same length as the shortest advertisement in its category (it is 24 in cars, 13 in clothing, 28 in digital, and 16 in food).

After normalization and extraction, the raw EEG signal is transformed into a 450 × 13 dimension vector, where each of the elements themselves contain a vector of data corresponding to the advertisement length. The 13 features include wavelength, time, and signal quality and etc. X is a 13 columns, 450 rows vector, $X_{450\times13}$ can be represented by 13 columns, i.e., $X_{450\times13} = [X_1, X_2, ...X_{13}]$, each vector is X_i where $i = 1, 2..., 12, 13$, then each column vector of X is listed in **Table 2**. However, in the experiment, selected columns X are used in the analysis, and they are Delta, Theta, Low Alpha, HighAlpha, LowBeta, HighBeta, LowGamma and HighGamma, Raw, Mediation and Attention, further selection details are in section 2.3.2.

2.3.2. Feature Selection and Label Selection

The map $Y = f(X)$ can be expressed as $label = f(features)$. It is implied by the equation that a different X and Y will result in different f, and different certainty profiles. Feature extraction and selection is, therefore, a very important process in machine learning

Feature selection can be classified into three types: flat features, stream features, and structured features (Tomasi and Kanade, 1991; John et al., 1994; Chowdhury and Lavelli, 2012). In the experiment, each feature of the input data is independent, hence features in the experiment are classified as flat.

The 13 features are grouped into different combinations to test their ability to predict purchasing chance. In the end, 11 features give the best prediction in the model. These grouped-features also corresponding to the literature that is related to emotion: Delta, Theta, LowAlpha, HighAlpha, LowBeta, HighBeta, LowGamma, and HighGamma (Klimesch, 1999; Teplan, 2002). Attention, Meditation and Raw values (see **Table 2** are also considered in the model because their physical meaning is related to emotion. Output data Y is the information of questionnaire answers. In this research, we are using the customer's questionnaire score to determine whether participants will strike an emotion to purchase the product. Each label Y represents different response/measure to the advertisement, if it is 1, it meant positive

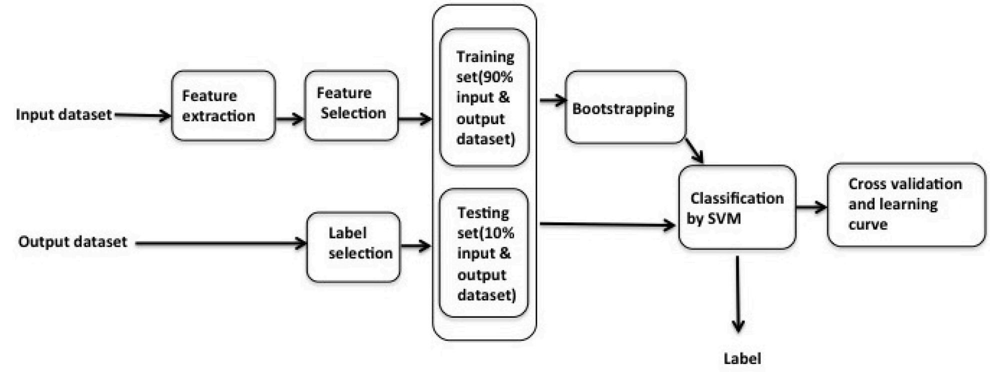

FIGURE 1 | In sample data pre-processing workflow: feature extraction and feature selection are applied in the input dataset to the training dataset, followed by the bootstrapping; label selection is applied in the testing dataset; classification by SVM then applied in the current testing and bootstrapped training dataset, the results of the classification are used to label the data and fed into the cross-validation and learning.

feedback is linked to emotion. Hence, we label the overall emotion as 1 (positive), and each label in the output data Y is independent. Different people can be influenced by different emotion, so we built a model that considers all emotions equally and then make the prediction. Questionnaire answers can be classified into two types: binary answers (yes or no answers) and ranked answers (values ranked between one and seven). All labels are selected and tested independently to see their significant impact on emotion. Due to the questionnaire answer types, labels are then grouped as binary answers, ranked answers and a combination of binary and ranked answers, each group's signification is also tested to the purchase possibility through emotion.

2.3.3. Data Augmentation via Bootstrapping

The original dataset contains 450 samples, and is a sparse dataset, and therefore bootstrapping is needed to increase the size of the dataset (Efron and Tibshirani, 1994; Efron et al., 2003). In the experiment, a dataset of twenty-nine people are used as in sample size of 435; while the other participant data of a sample size of 15 is used for out of sample testing. The 435 in sample size is too sparse to divide into a 90% training data (i.e., 393 samples) and a 10% testing data (i.e., 42 samples).

The in-sample data 391 samples are first divided into ten-folds under the condition that each fold has the same ratio of all type of answers in output data Y. Nine of the folds are used for training, while the tenth is used for testing, the ten folds algorithm is shown in Algorithm 2. Bootstrapping is used on each in sample training dataset. In bootstrapping process, Gaussian distribution bootstrapping method has been applied to each column in each training data X, shown in Algorithm 1. Gaussian process is a method to construct a parametric bootstrap approach from Bayesian non-parametric statistics, which implicitly considers the time-dependence of the data. (Efron, 1998) Many features are different frequency bands. Therefore, Gaussian is suitable also because it can generate continuous new data. However, Gaussian is a probability distribution between 0 and 1, while the data can be numbers even bigger than 1,000 and any number between 0 and 1 is too small to be the new bootstrapped number to be used in the experiment, hence in the bootstrapping process, a scalar has been calculated to multiply the probability, and the scalar is calculated as $scale = 0.5 \times (min + max)$, where the min represents the minimum number of that column, and the max represents the maximum number of that column. The new bootstrapped number is the original value plus the scaled Gaussian probability. In this way, the original data spreading will not be affected. Mathematical combination is then applied in the ninefold training data, which is shown in Algorithm 3. The corresponding output data Y is duplicated to match the size of bootstrapped training data X in each of the bootstrapping processes.

Algorithm 1 Bootstrapping1

procedure GAUSSIAN PROCESS BOOTSTRAP TO EACH COLUMN
  Input : Gaussian model, input data **Xtrain**
  Output : edited input data **Xp**
  ▷ Use Gaussian process regression bootstrap the whole **Xtrain** dataset, name as bootstrapping1
  for Each column in **Xtrain** as i **do**
    ▷ Edit **Xtrain** as **Xp**
    $\mathbf{Xp} = \mathbf{Xtrain}$
    ▷ select the maximum element
    $max = max(\mathbf{Xp}_i)$
    ▷ select the minimum element
    $min = min(\mathbf{Xp}_i)$
    $scale = 0.5 \times (min + max)$
    ▷ bootstrapping using Gaussian Distribution in $(-1, 1)$
    $bootc = scale \times Gaussian\_bootstrap(\mathbf{Xp}) + \mathbf{Xp}$
    ▷ update **Xp** with all new columns
    $\mathbf{Xp} = bootc$

2.3.4. Support Vector Machine

In literature, there are many different classification selection processes in machine learning. For example, Navie Bayes classifier, Random Forest, K-Nearest Neighbors, and Decision

Tree (Quinlan, 1987; Altman, 1992; Ho, 1995; Rennie et al., 2003). Support vector machine is a machine learning model used for classification and regression analysis (Aizerman et al., 1964; Boser et al., 1992; Jin and Wang, 2012). When SVM is used for classification, they separate a given set of binary labeled training data and a hyperplane that is maximally distance from them. Assume the input data is $\mathbf{x^j} = (x_1^j...x_n^j)$ be the realization of the random vector $\mathbf{x^j}$ While ϕ is the map mapping the feature space to a label space $\mathbf{y}$, where label space contains many vectors, mathematically label as $\{(\mathbf{x^1}, y^1), ...(\mathbf{x^m}, y^m)\}$. The SVM learning algorithm finds a hyperplane $(\mathbf{w}, b)$ such that the quantity

$$\gamma = min_t y^i\{< \mathbf{w}, \phi(\mathbf{x}^i) > -b\} \tag{1}$$

is maximized. In this equation, the dimension of ϕ is the same as the dimension of the label y and $< \mathbf{w}, f(\mathbf{x}^i) > -b$ corresponds to the distance between point $\mathbf{x^i}$ and the decision boundary. γ is the margin and b is a real number. The kernel of this function is $K_{i,j} =< \phi(x^i), \phi(x^j) >$. Given a new data x to classify, a label is assigned according to its relationship to the decision boundary, and the corresponding decision function is written as $f(x) = sign(< w, \phi(x) > -b)$.

In the experiment, as each label in the output is independent, and are binary (ranked answers are binarized via threshold as described below), therefore, regression that can end up with binary results are tested, i.e. non-linear regression, logistic regression and Support Vector Regression. All three methods have been utilized and proven appropriate in the previous research in EEG emotion detection (Schröder et al., 2001; Wang et al., 2011; Bejaei et al., 2015). However, Support Vector Machine is more appropriate on this type of sparse data (Wang et al., 2011). Besides, the experiment SVM has been shown to give the highest prediction accuracy result. The number of samples is larger than the number of features in our experiment, therefore the variable is chosen to reflect so; the loss function is set to 'Squared_hinge' because it is commonly used in classification and 'Squared_hinge' is convex and smooth and matches the function $0 - 1$, which is suitable for our experiment. 'Squared_hinge' is mathematically written as $(1 - yf(x))^2$. The map f is linear. Therefore the kernel is zero. Regularization is $L2$ as output data is no longer sparse, nor feature selection as features are targeted in output data (Ng, 2004).

In order to combine both binary and ranked answers, the rank answers are binarized using a thresholds according to the following rules:

- When the selected labels involve only the ranked answers, the threshold is set to be 3.5, 4 (i.e. $= (7 + 1)/2$) and 4.5.
- When the selected labels involve only binary answers, the threshold is set to be 0, 0.5 (i.e. $= (0 + 1)/2$ and 1.
- When the Threshold is a combination both types of answers, then the threshold can be written as equation: $Thre = \alpha * Thre_7 + \beta * Thre_2$, where α and β are the weights

2.3.5. Cross-Validation and Learning Curve

When the SVM model is built up, cross-validation and learning curve is used to assess whether the model is over-fitted or under-fitted (Geisser, 1993; Kohavi et al., 1995; Babyak, 2004; Frost, 2015).

Algorithm 2 Tenfolds

procedure TEN-FOLDS: IN SAMPLE TRAINING AND TESTING DATA SELECTION THROUGH INDEXES
 ▷ Ten-fold the whole dataset into ten sub dataset: same ratio of ones and zeros in nine subsets, combine the rest of unselected zeros and ones into the tenth subset
 Input : input data **X**, output data **Y**
 Output : nine different training input/output dataset $\mathbf{Xtrain_i}$
 ▷ Find the index of ones in the **Y**
 $index\_ones = index\_of\_ones(\mathbf{Y})$
 ▷ Find the index of zeros in the **Y**
 $index\_zeroes = index\_of\_zeroes(\mathbf{Y})$
 ▷ Calculate the ratio of ones in the length of **Y**
 $ratio = length(index\_ones)/length(\mathbf{Y})$
 ▷ After divide the **Y** into ten folds, find the number of ones in each fold
 $ones = round(ratio * length(\mathbf{Y})/10)$
 ▷ After divide the **Y** into ten folds, find the number of zeros in each fold
 $zeros = round((1 - ratio) * length/10)$
 ▷ Find the left over ones after first nine folds
 $ones\_left = length(index\_ones) - 9 * ones$
 ▷ Find the left over zeros after first nine folds
 $zeros\_left = length(index\_zeros) - 9 * zeros$
 ▷ In the tenth fold, append the selected index of zeros and ones
 $\mathbf{Xfold}[10] = append(\mathbf{X}[ones\_left], \mathbf{X}[zeros\_left])$
 $\mathbf{Yfold}[10] = append(\mathbf{Y}[ones\_left], \mathbf{Y}[zeros\_left])$
 for i in 0:9 **do**
  ▷ Find the **Y** index of ones in each fold
  $selection\_ones = index\_of\_ones[i*ones:(i+1)*ones]$
  ▷ Find the **Y** index of zero in each fold
  $selection\_zeros = index\_of\_zeros[i * zeros:(i + 1) * zeros]$
  ▷ Find the **Y** index in each fold
  $selection = append(selection\_ones, selection\_zeros)$
  ▷ Find the **Yfold** that is corresponding to the selected column index in **Y**
  $\mathbf{Yfold}[i] = \mathbf{Y}[selection]$
  ▷ Find the **Xfold** that is corresponding to the selected column index in each **X**
  $\mathbf{Xfold}[i] = \mathbf{X}[selection]$
 ▷ **Xtrain** and **Ytrain** is achieved by appending any nine of ten subsets in Xfold and Yfold
 $\mathbf{Xtrain} = append(\mathbf{Xfold}[C(10, 9)])$
 $\mathbf{Ytrain} = append(\mathbf{Yfold}[C(10, 9)])$

3. RESULT

3.1. Behavior Result

In this model, we use labels and EEG signals as variables, and emotion is the hidden variable bridge labels and EEG signals, they can be written as $Y = f(X|E)$, where E is emotion. The result of this experiment shows that if we have an individual's EEG

Algorithm 3 Bootstrapping2

procedure BOOTSTRAPPING THE TRAINING X DATASET FROM TENFOLDS USING MATHEMATICAL COMBINATION
  Input : input data **Xtrain**
  Output : nine different training input dataset $\mathbf{X2_j}$
  ▷ Start with the original dataset **Xtrain**, but edit the selected column by the corresponding column in algorithm1
  $\mathbf{X2} = \mathbf{Xtrain}$
  for Each column in **X2** as j **do**
    ▷ make a copy of $\mathbf{X2}_j$ for editing
    $column = \mathbf{X2_j}$
    for r in $range(1, 12)$ **do**
      ▷ generate all unique iterations of *column* using *nCr* method, and then replace the corresponding index in the **Xtrain** while the rest of the columns remain the same
      $newdata = nCriterations(12, r, row)$
      $\mathbf{X2_j} = replace\_bootstrapping1(\mathbf{Xtrain}[j]\_replace\ \mathbf{Xp}[newdata])$

signal, which has been collected from the single electron device after watching the advertising, the accuracy of predicting if this individual would or not make a purchase of the corresponding product in the advertising is around 75% based on the SVM model. In the experiment, each participant has been selected as the out sample data, and then the rest of the participants are in sample data (90% of in sample data is the training dataset, while the 10% of the in-sample data is the testing dataset, bootstrapping has been applied to the 90% in sample training dataset.

The accuracy of prediction using SVM over the ranked answers is 77.28%. In this setting, the threshold of ranked answers results is 4. The recall score of this model is 72% and the F score for this model is 75%. In the same threshold of ranked answers result is 4, each category prediction is: the likelihood of purchasing the car is 63.5%, the likelihood of purchasing the cloth is 92.3%, the likelihood of purchasing the digital is 68.5% and the likelihood of purchasing the food is 82.76% (**Table 3**).

The accuracy of prediction using SVM model over combined ranked and binary answers is 75.4% under the conditions that ranked and binary answers have equal weighting (of 0.5), the threshold of ranked answers is 4, the threshold of a binary answer is 0.4, the threshold of the whole dataset is 0.4 (**Table 8**). The recall score of this model is 69% and the F score for this model is 71%. In the same experiment setting, each category prediction is: the likelihood of purchasing the car is 59.6%, the likelihood of purchasing the clothes is 92.3%, the likelihood of purchasing the digital is 64.8% and the likelihood of purchasing the food is 81.03% (**Tables 4–7**).

This indicates that EEG collected using single-electrode wearable devices is above 70% accuracy for prediction whether customers would purchase the product after watching the advertisement, and it can achieve higher accuracy prediction and reach about 75%.

The out of sample predictions are tested in two cases, and in each case, the results are the average/mean of picking up different thirty individual participants as out sample test. When it is only ranked answers, if the samples from the remaining participant from all four categories are combined into one dataset, then the prediction of purchasing power can reach 72.4%; if each product category is tested, then the car purchasing power can reach up to 50.09%, the clothing purchasing power can reach 78.01%, the digital products purchase power can reach 56.56% and the food purchase power can reach 69.34%. When it is the combined result of ranked and binary answers, if the samples from the remaining participant from all four categories are combined into one dataset, then the prediction of purchasing power can reach 71.2%; if each product category is tested, then the car purchasing power can reach up to 51.8%, the clothing purchasing power can reach 65.9%, the digital products purchase power can reach 57.2% and the food purchase power can reach 60.62%.

Also, in the research, each label Y has been tested, but it is a difficult test and the result is not balanced, the recall and F scores are both low, that is why those predictions are not mentioned in the results. Different thresholds for each model have also been tested during the experiment, however, they are not good enough to accurately explain the model.

Seventy-five percentage is a relatively high result to judge the purchasing power based on the EEG signal after watching the advertising, though there is no research on the direct link of EEG

TABLE 3 | Accuracy prediction of the ranked answer to different type of product at different thresholds.

Product type	Threshold 3.5	Threshold 4	Threshold 4.5
Car	0.365384615385	0.634615384615	0.826923076923
Food	0.603448275862	0.827586206897	0.931034482759
Digital	0.388888888889	0.685185185185	0.87037037037
Clothes	0.673076923077	0.923076923077	0.961538461538
All dataset	0.595090082962	0.772837217714	0.898908153808

TABLE 4 | Likelihood of purchasing the car in the combined answer model at different thresholds.

Threshold to each type answer in car	Threshold of the car dataset		
	Thre = 0.4	*Thre* = 0.5	*Thre* = 0.6
$Thres_7 = 0.4$, $Thres_2 = 3.5$	0.365384615385	0.365384615385	0.826923076923
$Thres_7 = 0.4$, $Thres_2 = 4$	0.596153846154	0.596153846154	0.865384615385
$Thres_7 = 0.4$, $Thres_2 = 4.5$	0.75	0.75	0.903846153846
$Thres_7 = 0.5$, $Thres_2 = 3.5$	0.365384615385	0.365384615385	0.903846153846
$Thres_7 = 0.5$, $Thres_2 = 4$	0.634615384615	0.634615384615	0.903846153846
$Thres_7 = 0.5$, $Thres_2 = 4.5$	0.807692307692	0.807692307692	0.923076923077
$Thres_7 = 0.6$, $Thres_2 = 3.5$	0.365384615385	0.365384615385	0.980769230769
$Thres_7 = 0.6$, $Thres_2 = 4$	0.634615384615	0.634615384615	0.980769230769
$Thres_7 = 0.6$, $Thres_2 = 4.5$	0.807692307692	0.807692307692	1

TABLE 5 | Likelihood of purchasing the food in the combined answer model at different thresholds.

Threshold to each type answer in food	Threshold of the food dataset		
	***Thre* = 0.4**	***Thre* = 0.5**	***Thre* = 0.6**
$Thres_7 = 0.4$, $Thres_2 = 3.5$	0.603448275862	0.603448275862	0.965517241379
$Thres_7 = 0.4$, $Thres_2 = 4$	0.810344827586	0.793103448276	0.965517241379
$Thres_7 = 0.4$, $Thres_2 = 4.5$	0.913793103448	0.913793103448	0.98275862069
$Thres_7 = 0.5$, $Thres_2 = 3.5$	0.603448275862	0.603448275862	0.98275862069
$Thres_7 = 0.5$, $Thres_2 = 4$	0.827586206897	0.827586206897	0.98275862069
$Thres_7 = 0.5$, $Thres_2 = 4.5$	0.931034482759	0.931034482759	1
$Thres_7 = 0.6$, $Thres_2 = 3.5$	0.603448275862	0.603448275862	0.948275862069
$Thres_7 = 0.6$, $Thres_2 = 4$	0.827586206897	0.827586206897	0.948275862069
$Thres_7 = 0.6$, $Thres_2 = 4.5$	0.931034482759	0.931034482759	0.948275862069

TABLE 6 | Likelihood of purchasing the digital in the combined answer model at different thresholds.

Threshold to each type answer in digital	Threshold of the digital dataset		
	***Thre* = 0.4**	***Thre* = 0.5**	***Thre* = 0.6**
$Thres_7 = 0.4$, $Thres_2 = 3.5$	0.407407407407	0.407407407407	0.944444444444
$Thres_7 = 0.4$, $Thres_2 = 4$	0.648148148148	0.648148148148	0.962962962963
$Thres_7 = 0.4$, $Thres_2 = 4.5$	0.814814814815	0.814814814815	0.981481481481
$Thres_7 = 0.5$, $Thres_2 = 3.5$	0.388888888889	0.388888888889	0.981481481481
$Thres_7 = 0.5$, $Thres_2 = 4$	0.685185185185	0.685185185185	0.981481481481
$Thres_7 = 0.5$, $Thres_2 = 4.5$	0.87037037037	0.87037037037	0.981481481481
$Thres_7 = 0.6$, $Thres_2 = 3.5$	0.388888888889	0.388888888889	0.981481481481
$Thres_7 = 0.6$, $Thres_2 = 4$	0.685185185185	0.685185185185	0.981481481481
$Thres_7 = 0.6$, $Thres_2 = 4.5$	0.87037037037	0.87037037037	NA

TABLE 7 | Likelihood of purchasing the clothes in the combined answer model at different thresholds.

Threshold to each type answer in clothes	Threshold of the clothes dataset		
	***Thre* = 0.4**	***Thre* = 0.5**	***Thre* = 0.6**
$Thres_7 = 0.4$, $Thres_2 = 3.5$	0.653846153846	0.653846153846	1
$Thres_7 = 0.4$, $Thres_2 = 4$	0.923076923077	0.923076923077	1
$Thres_7 = 0.4$, $Thres_2 = 4.5$	0.961538461538	0.961538461538	1
$Thres_7 = 0.5$, $Thres_2 = 3.5$	0.692307692308	0.692307692308	1
$Thres_7 = 0.5$, $Thres_2 = 4$	0.923076923077	0.923076923077	1
$Thres_7 = 0.5$, $Thres_2 = 4.5$	0.961538461538	0.961538461538	1
$Thres_7 = 0.6$, $Thres_2 = 3.5$	0.692307692308	0.692307692308	0.980769230769
$Thres_7 = 0.6$, $Thres_2 = 4$	0.923076923077	0.923076923077	0.980769230769
$Thres_7 = 0.6$, $Thres_2 = 4.5$	0.961538461538	0.961538461538	0.980769230769

TABLE 8 | Likelihood of purchasing in the combined answer model at different thresholds.

Threshold to each type answer in whole dataset	Threshold of the whole dataset		
	***Thre* = 0.4**	***Thre* = 0.5**	***Thre* = 0.6**
$Thres_7 = 0.4$, $Thres_2 = 3.5$	0.6044	0.60022153401	0.940276239347
$Thres_7 = 0.4$, $Thres_2 = 4$	0.754142459932	0.758595745643	0.950177453263
$Thres_7 = 0.4$, $Thres_2 = 4.5$	0.866265795601	0.866265795601	0.968578339399
$Thres_7 = 0.5$, $Thres_2 = 3.5$	0.595090082962	0.595090082962	0.977326672243
$Thres_7 = 0.5$, $Thres_2 = 4$	0.772837217714	0.772837217714	0.977326672243
$Thres_7 = 0.5$, $Thres_2 = 4.5$	0.894454868097	0.894454868097	0.977326672243
$Thres_7 = 0.6$, $Thres_2 = 3.5$	0.595090082962	0.595090082962	0.977326672243
$Thres_7 = 0.6$, $Thres_2 = 4$	0.772837217714	0.772837217714	0.977326672243
$Thres_7 = 0.6$, $Thres_2 = 4.5$	0.894454868097	0.894454868097	0.977326672243

signal and purchase intention. However, research has been done on using emotions to quantify the purchasing power. In 2006, John Pawle and Peter Cooper showed that emotional factors to brand decision making range from 63 to 85% (Tsai, 2005; Pawle and Cooper, 2006).

3.2. Cross-Validation and Learning Curve

The two models with the whole dataset are selected to draw the cross-validation and learning curve. The reasons for only selecting these two are they give the best prediction results, and they are directly related to the paper hypothesis: predicting the likelihood of customers purchasing the products.

The cross-validation and learning curve is shown in **Figures 2**, **3**.

Figure 2 shows the cross-validation and learning curve when only the ranked answers are selected. **Figure 3** shows the cross-validation and learning curve when the thresholds of ranked

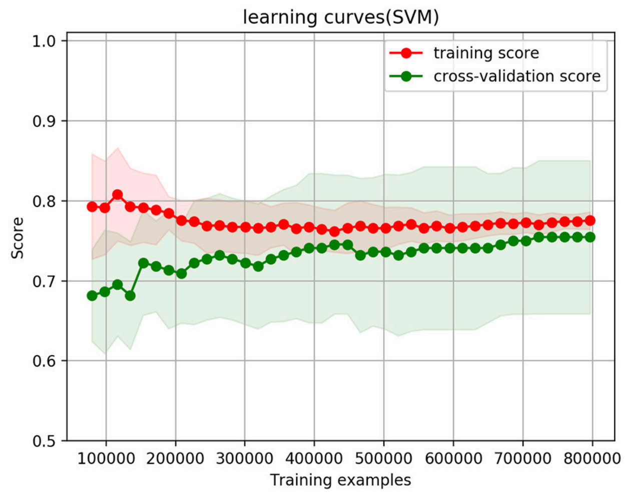

FIGURE 2 | Cross validation curves when only ranked answers are selected, with a threshold of 4.

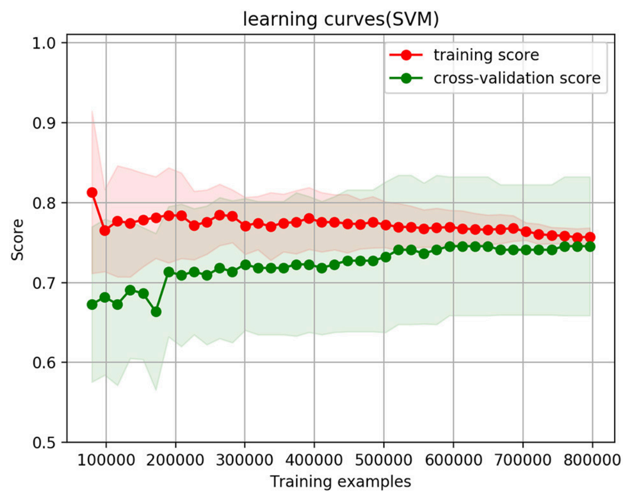

FIGURE 3 | Cross-validation curves when thresholds of ranked answers is 4 and binary answers threshold is 0.4, their weight is equal at 0.5, and the whole dataset thresholds is 0.4.

answers is 4, and binary answers threshold is 0.4, their weight is equal at 0.5, and the whole dataset thresholds is 0.4. In both figures, the X-axis represents the size of training examples; Y-axis represents the accuracy prediction score. The red lines represent the training score, and green lines represent cross-validation score/testing score.

In the ranked answers only case in **Figure 2**, training and testing curves converge to 77.28%; when the combination of ranked answers and binary answers are selected (ranked answers threshold is 4, and binary answers threshold is 0.4), as shown in **Figure 3**, the training and testing curves converge to 75.4%. The shaded red and shaded green are standard deviations at confidence interval 10% to its corresponding training score and corresponding testing score. Mathematically, they are calculated as $(training_{mean} - training_{std}, training_{mean} + training_{std})$ and $(testing_{mean} - testing_{std}, testing_{mean} + testing_{std})$. Both figures show that the training curves are slightly over-fitting at the beginning, but it gradually decrease and reach a stable point with the decreasing variance. In testing curves, the variance remains approximately the same from the beginning till the end throughout the training example size increases; it remains the same because the testing data size does not change regardless of how training example size changes. Convergence of training and testing curves means there is no over-fitting and no under-fitting issues of the model; the SVM model we set up and use therefore performs well.

4. DISCUSSION

The approximately 75% accuracy prediction and the converging cross-validation curve result together show that the EEG signal and edited AIDA metrics model we found is a suitable model. This result is sufficient to declare EEG a useful dataset to collect in the advertising industry.

Further improvements can be made to the accuracy of prediction through improving the chosen thresholds and increasing the study sample size rather than relying on bootstrapping. The accuracy of prediction may be further improved through selecting both male and female participants and gender-neutral products and their advertisement.

The statistical results show that the ranked answers with a threshold of 4 has a better result than the combined rank and binary answers, with about 2% more accuracy. It also shows that each category prediction is lower than the whole dataset prediction in both models. It shows products like cars have the lowest accuracy of prediction and clothes have the highest accuracy of prediction among the four categories. This may be caused by cars being a costly product, and the decision to purchase one depends more on lifestyle and personal circumstance than advertising. In this case, the prediction accuracy can be improved by pre-selecting participants to control for these factors, or by adjusting predictions based on the personal circumstances. In the experiment, the F scores and the recall scores are also good in the model; it happens to be consistent that the whole dataset scores are better than each category dataset. The out of sample test result is not as good as the sample test, but it is acceptable, which further indicates the model is good.

In the current research, the emotions and opinions of the user have been used as a hidden variable to bridge EEG signal and self-reported metrics to evaluate the impact of advertisement and its power to influence purchasing. In the literature, research has been done on the relationship of Theta wavelength with emotion and the relationship of Beta Wavelength with emotion (Lucchiari and Pravettoni, 2012; Wang et al., 2016). Considering that EEG signals contain components at many other frequencies, it is worth further investigation of the relationship between EEG signal and emotion, and how they impact a decision to make a purchase.

In past attempts, an AIDA model has been used to quantify emotion metrics in terms of scores for attention, interest, desire and action aspects after watching the advertisement (Strong, 1925). In our research, we follow the idea of the AIDA model and add additional dimensions to quantify these emotions to achieve a more precise measure. The ranked and binary answers have equal waiting in accordance with the AIDA model and literature mentioned in section 2.1 which considers all labels with equal impact. It is also interesting to further execute a non-parametric machine learning model to assess the importance of each label or a grouping of similar labels for purchasing power. More details on the emotion model our experiment uses are described in section 2.1.

This is a new method in Neuromarketing. The advantage of this method is to be able to assess impact fast. The model, once found, can work in real-time on EEG signals, in a highly automated way. Something not possible in traditional methods that involve data collection via surveys or discussion, and then analysis, which requires both time and man-power to accomplish; or assessing the impact through sales figures afterwards, which can be easier to automate, but has much longer cycle times.

Our proposed evaluation method also shows less bias due to EEG data being involuntary and therefore not subject to conscious and experimental bias. Unlike in a focus group study conducted by an advertisement company, the study in an academic setting removes the potential for study biases in which participants tend to give kinder answers than they may think, out of goodwill or some sense of social obligation (De Pelsmacker et al., 2002; Maison et al., 2004; Shen and Li, 2009). The questionnaire questions are written neutrally, and asks similar questions from slightly different angles to validate consistency. Because these questions yield consistent results, it indicates a high likelihood that they represent the true thought of participants. The questions in the questionnaire do not include identifiable or confidential information of any individual; therefore removing potential reasons for participants to hide their true opinion.

Furthermore, the device used in this research is a single-electrode wearable device that is low cost, portable, and easy to use, allowing this kind of data collection to be scaled much more rapidly than machines traditionally associated with functional brain imaging in neuroscience, such as traditional clinical-grade multi-channel EEG setups, and fMRI (Signal, 2015). Multiple types of EEG devices have been studied in the literature and applied to neuromarketing studies; the results do not show an appreciable improvement in accuracy of multi-channel EEG systems vs. single electrode EEG systems (Hamzy and Dutta, 2000; Liu et al., 2013). Therefore, single electrode EEG devices is sufficient for the experiment, and the ease of use of a simple, self-contained and battery-operated wearable device opens up new kind of customer engagement opportunities where their EEG can be recorded throughout the day in settings that are much more normal than would be the case in a lab setting, removing any influence that may come from the experimental setup.

The most significant part of this research is the extension of modeling emotions with a single-wavelength collected from EEG to multidimensional wavelengths, allowing the extraction of more informational content from EEG than previously attempted.

The result of this research can be further applied to individual consumers behavior; to allow the advertising industry to tailor their advertisement for maximum impact; and adapted to work for TV an movie studios to predict viewership rates of movies and TVs from trailers.

5. CONCLUSION

We proposed a model that can use EEG signals measured using low-cost consumer-grade EEG headsets taken while a consumer watches an advertisement, to rapidly predict the consumer’s likelihood of purchasing the product. While further research can be made on the selection of thresholds, and the quality of the result can be improved with the collection of larger datasets, the method as shown is nevertheless easy to deploy, yields rapid results, scales better than any existing method, and introduces less experimental and environmental bias. If employed in place of existing focus-group studies, any company involved in mass-media advertising stands to improve the effectiveness of their advertising, improve estimates of the impact on sales of their advertising, and be more informed when building their advertising strategy, leading to increased ROI.

ETHICS STATEMENT

The experiment was carried out at ZheJiang University and the approval was obtained from the Ethics committee at the ZheJiang University, China. In addition, written informed consent forms were obtained from all volunteers before the experiment started. The ethics approval number from ZheJiang University is NSL20 160012.

AUTHOR CONTRIBUTIONS

ZW carried out the experiment and wrote the paper. CW and AS edited the paper. PW prepared the experiment. XW prepared the experiment data and provided advice with some of the editing. YG supervised the project.

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frontiers in Neuroscience

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Frontal Brain Asymmetry and Willingness to Pay

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Consumers frequently make decisions about how much they are willing to pay (WTP) for specific products and services, but little is known about the neural mechanisms underlying such calculations. In this study, we were interested in testing whether specific brain activation—the asymmetry in engagement of the prefrontal cortex—would be related to consumer choice. Subjects saw products and subsequently decided how much they were willing to pay for each product, while undergoing neuroimaging using electroencephalography. Our results demonstrate that prefrontal asymmetry in the gamma frequency band, and a trend in the beta frequency band that was recorded during product viewing was significantly related to subsequent WTP responses. Frontal asymmetry in the alpha band was not related to WTP decisions. Besides suggesting separate neuropsychological mechanisms of consumer choice, we find that one specific measure—the prefrontal gamma asymmetry—was most strongly related to WTP responses, and was most coupled to the actual decision phase. These findings are discussed in light of the psychology of WTP calculations, and in relation to the recent emergence of consumer neuroscience and neuromarketing.

Keywords: willingness to pay, electroencephalography, neuroimaging, consumer neuroscience, neuromarketing, neuroeconomics

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INTRODUCTION

How do we decide how much we are willing to pay for a product? What are the basic mechanisms underlying such computations? In economics and the consumer sciences, one central concept in this regard is the Willingness To Pay (WTP), defined as the maximum amount of resources that a consumer is willing to give up in exchange for an object or service being sold (O'Brien and Viramontes, 1994; Homburg et al., 2005). Research has linked WTP to the evaluation to subsequent consumer motivation and real consumption choice in as diverse consumer choices as health services (Olsen and Smith, 2001), organic and healthy food products (Misra et al., 1991), country of origin effects (Loureiro and Umberger, 2003), and products that are either seen as environmentally friendly or otherwise ethically sound (Ozanne and Vlosky, 1997; Vlosky et al., 1999; De Pelsmacker et al., 2005).

Despite the study of WTP in such a variety of situations, little is known about the underlying neural or psychological processes of these calculations. Recent calls for an improved understanding of the basic mental mechanisms underlying WTP calculations have proposed to include neurobiological explorations of how the brain calculates values and instigates choice behavior.

Still, in spite of the rapidly expanding research fields of neuroeconomics (Rolls, 2000; Camerer et al., 2005, 2016; Kenning and Plassmann, 2005; Rustichini, 2005; Kable and Glimcher, 2009; Wilhelms and Reyna, 2014; Levy and Glimcher, 2016), neuromarketing or consumer neuroscience (Ariely and Berns, 2010; Fisher et al., 2010; Plassmann et al., 2012, 2015; Smidts et al., 2014; Ramsøy, 2015; Hsu, 2017; Lee et al., 2017). In these multidisciplinary efforts, any exact understanding of the neural or psychological mechanisms underlying WTP calculations is still woefully lacking (Plassmann et al., 2012). In a study by Plassmann et al. (2007) it was found that activation in both the right ventromedial prefrontal cortex (vmPFC) and the right dorsolateral PFC (dlPFC) demonstrated a significant relationship to subjects' WTP. However, as the researchers noted, the exact role of the OFC and dlPFC in the calculation of WTP could not be determined. Notably, the authors speculated that based on the different connectivity that the two brain regions have, the multisensory nature of OFC could point to a role in the immediate valuation of items (Rolls, 2000, 2004), while the dlPFC could be more involved in the execution of choice behavior (Petrides and Pandya, 1999). More recent accounts also support a dissociation between value calculation and choice execution (and choice conflict) between the OFC and regions such as the ACC and dlPFC (Plassmann et al., 2010; Rushworth et al., 2012).

The study reported here was set up to explore the possible role of prefrontal hemispheric differences in computing WTP. The notion that the computation of WTP may rely on a diverse contribution from the two hemispheres is rooted in a growing body of work demonstrating a prefrontal asymmetry in relationship to approach and avoidance behaviors. The main findings emerging from this research are that approach behaviors are related to a relative stronger engagement of the left PFC compared to the right PFC (Pizzagalli et al., 2005), and that such effects are mainly due to motivation and not valence (Harmon-Jones and Allen, 1998). The left-hemispheric dominance for approach behaviors has also been suggested in studies of consumer choice (Ravaja et al., 2012), as well as advertising (Ohme et al., 2009, 2010). However, there is still conflicting evidence with regard to the hemispheric asymmetry model (Spielberg et al., 2008), and studies on the inverse effect of stronger relative engagement of the right compared to left PFC in avoidance behavior has been less consistent (Harmon-Jones and Allen, 1998). Interestingly, in the Plassmann et al. study we cited above (Plassmann et al., 2007), although the subjects were not explicitly tested for prefrontal asymmetry, the increased activations in the vmPFC and dlPFC were exclusively located in the right hemisphere.

In the present study, by asking subjects to watch images of different products while prefrontal asymmetry was assessed using electroencephalography (EEG), we find that a prefrontal laterality index obtained during passive product viewing is highly related to subsequent WTP reports. Notably, while prior EEG studies have focused on prefrontal asymmetry effects using alpha frequency, our results show that gamma frequency and beta frequency can have equal or even stronger relationship to choice behavior.

Abbreviations: EEG, electroencephalography; WTP, Willingness to Pay; PAI, Prefrontal Asymmetry Index.

MATERIALS AND METHODS

Sixteen women (age range 19–51, mean/std = 27.1/8.2, all right handed) were recruited using both online (www.forsoegsperson.dk and www.videnskab.dk) and direct recruitment procedures. The study reported here was part of a larger cohort study on compulsive consumption ($n = 63$), but for the present study we only included subjects who did not meet diagnostic criteria for compulsive consumption, or the preclinical compensatory consumption stage, as assessed by the Compulsive Buying Scale (Faber and O'Guinn, 1992). All subjects read and signed an informed consent, and were initially informed and trained with the experimental procedure. The study was approved by the local ethics committee (at Copenhagen Business School) and abided to the regulations of the Declaration of Helsinki.

Experimental Design

Subjects were placed in front of a screen running with a 1,920 × 1,200 pixel screen resolution, and were placed at an approximate distance of 60 cm from the screen. During the test, subjects first saw a fixation cross for 3 s, followed by an image of a product from one of four categories; bags, clothes, women's shoes, and fast-moving consumer goods (FMCG). The individual product was shown for 3 s, after which asked to report how much they would like to pay for the product, using an on-screen visual analog scale ranging from zero to 2,000 Danish Kroner (≈$330). The experimental design is illustrated in **Figure 1**. In total, each participant was exposed to 40 trials, 10 trials in each product category (bags, clothes, FMCG, shoes). To increase the external validity of the test, subjects were instructed that the choices from two of the subjects from the cohort would be randomly selected and given 1,500 DKK each, and that five of each subject's choices would be randomly selected, and the product receiving the highest bid of those five would be realized. Should the highest bid not amount to 1,500 DKK, they would be paid the remaining amount in cash. This meant that subjects were motivated to optimize their product choices, which allowed us to better estimate the actual WTP, instead of subjective estimates of WTP. While this approach allowed the opportunity for participants to employ certain decision strategies such as selecting the minimally possible difference in price to signify preference (e.g., 2 DKK for the preferred item, relative to 1 DKK for non-preferred items) and retain the remaining amount in cash, no such strategy was found in the WTP choices made. In total, 640 observations were made (16 participants, 40 WTP decisions each).

Since the WTP scores were not normally distributed (Kolmogorov-Smirnov-Lilliefors test $D = 0.276$, $p < 0.01$), we chose to log transform the WTO score to achieve normal distribution of the WTP data, thus providing a logWTP score (producing a normal distribution of KSL test $D = 0.071$, $p = 0.201$), which we used in all analyses.

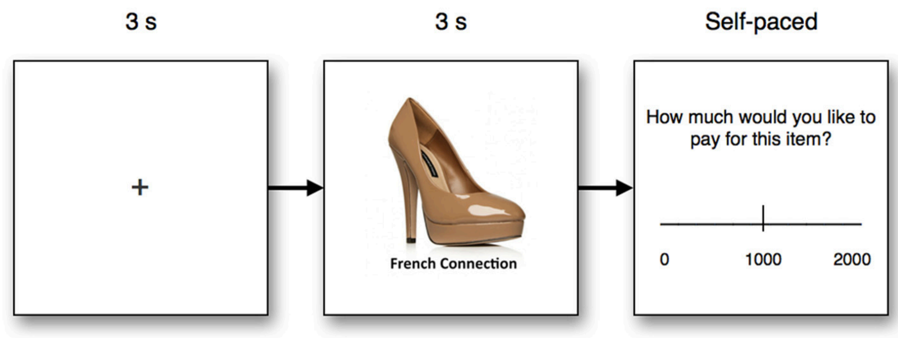

FIGURE 1 | Experimental design. Subjects first saw a fixation cross for 3 s, followed by a product with accompanying brand information for 3 s. The product image was accompanied by the brand name of the product. Finally, subjects chose the amount of money (Danish kroner) they were willing to pay for the product using a visual analog scale, and in a self-paced manner.

Neuroimaging

Neural responses were recorded using a wireless 14 channel headset (Emotiv EPOC Inc.) with a sampling rate of 128 Hz (bandwidth = 0.2–43 Hz, digital notch filters at 50 and 60 Hz, and with built-in digital 5th order Sinc filter) and electrodes positioned at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 (the 10–20 system, see **Figure 2**). The headset was connected to a PC running Windows 7 and transmitted data wirelessly to a USB receiver module. Stimulus presentation and data collection for behavioral responses and neuroimaging data was performed using Attention Tool 4.5 (iMotions, www.imotionsglobal.com).

Offline data processing was carried out using the EEGLAB toolbox in Matlab. Baseline correction was performed on the entire recording to minimize potential drifts of electrodes. To avoid influence of bad channels affecting the analysis, the quality of each electrode was evaluated during the whole recording. Channel quality was provided for each sample with the Attention Tool 4.5 software with a categorization between 1 and 4 corresponding to no connection (poor) to good contact, respectively. In the analysis we declared an electrode as bad if the channel quality did not fulfill a criterion of having minimum 95% good channel quality during the whole recording. Bad channels were rejected from further analysis. In this study, we observed an average signal quality of 84.42 ± 0.20 st.dev percent, with some channels providing 100% average signal quality (AF3, F7, T7, and F8) while other channels produced the lowest average signal quality, and with large variation across individuals (average ± st.dev: O1 = 46.92 ± 49.91%, O2 = 41.06 ± 49.19%). The channels of most interest for this study produced signal quality well above acceptable levels (F3 = 82.40 ± 38.08%, F4 = 94.13 ± 23.50%). Only participants with valid data for the F3 and F4 electrodes were used in the study.

Power spectra were calculated on each electrode using windows of 50 samples (i.e., 390 ms) with a 80% overlap and a frequency resolution of 1 Hz. The power spectra were reduced to frequency bands in accordance with the alpha, beta, and gamma frequency bands, defined as alpha [8–13 Hz], beta [13–25 Hz], and gamma [25–40 Hz]. Each band was calculated as a summation of the total power within the band.

For each electrode alpha, beta and gamma frequencies were included in the analysis. The prefrontal asymmetry index (PAI) was calculated by subtracting the values from the AF4 (right prefrontal) electrode from the AF3 (left prefrontal) electrode, and divided by the sum of the two electrodes. This is illustrated by the following formula:

$$\frac{\log(AF_3) - log(AF_4)}{\log(AF_3) + log(AF_4)}$$

This means that for gamma (PAI_γ) and beta (PAI_β) frequencies, more positive values would be indicative of stronger engagement of the left PFC, and that more negative values would be related to relative stronger engagement of the right PFC. The frontal asymmetry was corrected for overall brain engagement by dividing the F3/F4 ratio on the sum of both channels (F3+F4). The alpha frequency has been linked to inhibitory brain function and is thus assumed to be negatively related to neural activation levels (Başar et al., 2001; Palva and Palva, 2007). The alpha measure (PAI_α) has an inverse sign to that of gamma and beta; thus, more negative values would be indicative of relative stronger engagement of the left PFC.

We first ran a mixed model with logWTP as the dependent variable, with the prefrontal asymmetry for each frequency (PAI_α, $PAI_{\beta,}$ and PAI_γ) for the aggregate response of the 3 s product viewing time as independent variables, and with subject as random factor. To increase the specificity of the prefrontal activation, all alpha, beta, and gamma electrode values (F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, and F8) were modeled as regressors of no interest. This was imposed to increase the specificity of the frontal asymmetry measure.

Following this, we tested whether the inclusion of product type would improve the overall explanatory value of the model. To this end, we ran a new mixed model analysis with logWTP as the dependent variable, and with product category (FMCG, clothing, shoes, bags), prefrontal asymmetry (PAI_α, PAI_β, and PAI_γ) and the category*PAI interactions as independent variables, again with subject as random factor.

To record and correct for the degrees of freedom used in denominator of each test, we use the term "Degrees of Freedom

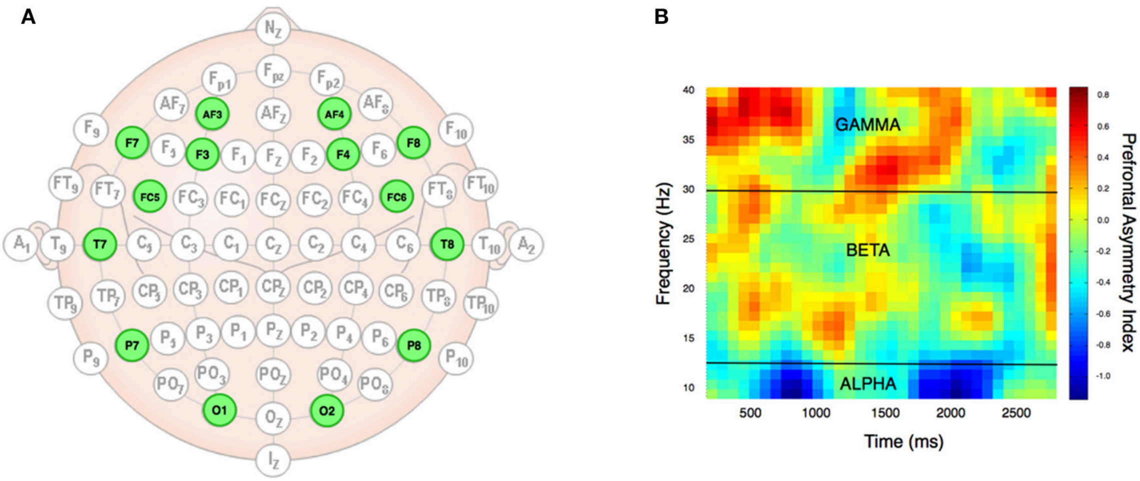

FIGURE 2 | EEG setup and data types. The electrodes were positioned bilaterally according to the 10/20 system **(A)** at 14 specific locations (highlighted in green). From the raw EEG data, Fourier transformation provided alpha, beta, and gamma frequency bands, which allowed analysis of prefrontal asymmetry over time in these three different frequency domains, as exemplified by data from a single subject **(B)**. The **(B)** plot was achieved by running the PAI analysis on the frequency bands from 10 to 40 with an increment of 1 Hz (y-axis), and over time with a range from 100 to 3,000 ms with increments of 100 ms (x-axis). The heat map indexes the prefrontal asymmetry normalized as z-scores. Yellow to red colors denote positive PAI score, while cyan to blue colors denote low PAI scores. Black lines indicate frequency band borders of alpha, beta, and gamma.

for the Denominator" (DFDen). The DFDen is calculated using the Kenward–Roger first order approximation (Kenward and Roger, 1997), and shows the denominator degrees of freedom for the effect test (the degrees of freedom for error).

We were interested in testing whether the relationship between prefrontal asymmetry and WTP would be modulated by stimulus duration (and, consequently, the time to decision). We therefore ran a mixed model analysis with logWTP (hereafter WTP) as the dependent variable, and with time, prefrontal asymmetry (PAI_α, PAI_β, and PAI_γ) and the time*PAI interactions as independent variables, and with subject as random factor.

Finally, to test for other types of EEG responses related to WTP, we tested the relationship between all electrodes in the alpha, beta and gamma frequency bands, and their relationship to WTP, using a mixed model where logWTP was the dependent variable, each electrode alpha, beta, and gamma values were used as independent variables, subject was used as a random factor, and product category as a regressor of no interest.

RESULTS

Products received an average WTP of 202.25 Danish Kroner (DKK), but also demonstrated a large variance (STD = 339.36; range = 0:1627.9 DKK). There was a significant difference between the four product categories in logWTP score ($R^2 = 0.452$, $F = 41.1$, $p < 0.0001$) that was driven by a lower logWTP for FMCG (4.51 ± 0.01) than the other product categories (bags = 6.33 ± 0.01; clothing = 6.03 ± 0.01; shoes = 5.98 ± 0.01).

In our first mixed model analysis, we tested the effect of prefrontal asymmetry during product viewing on subsequent WTP. The overall model was significant ($R^2 = 0.267$, RMSE = 0.999, $F = 5.37$, $p = 0.0013$). As **Table 1** shows, only PAI_γ showed a statistically significant effect, while PAI_β was trend significant, and PAI_α did not produce a significant result.

Looking at the individual effects, and as shown in **Figure 3**, (PAI_γ $R^2 = 0.270$, RMSE = 0.996, estimate = 0.161, $t = 2.92$, $p = 0.0038$) was positively related to WTP, i.e., more positive values were related to higher WTP. Similarly, PAI_β, although not reaching statistical significance, showed a trend for a positive relationship to WTP ($R^2 = 0.273$, RMSE = 0.993, estimate = 0.161, $t = 1.67$, $p = 0.0967$), which means that stronger engagement of the left PFC in beta frequency band was related to higher WTP. Finally, PAI value in the alpha range ($R^2 = 0.276$, RMSE = 0.992, estimate = −0.085, $t = -1.07$, $p = 0.2858$) was negatively related to WTP, but did not produce a significant result. Although not significant, this result lends support to the frontal asymmetry and WTP, as more negative PAI_α values (i.e., stronger relative engagement of the left PFC, due to the inverse aspect of the alpha frequency relative to brain activity) were related to higher WTP scores.

When analyzing PAI_α, PAI_β, and PAI_γ independently, the relationship was significantly for PAI_β and PAI_γ only (alpha: $t = -1.07$, $p = 0.286$; beta: $t = 2.11$, $p = 0.036$; gamma: $t = 3.55$, $p = 0.0004$). Further analyses into the relationship between the three asymmetry scores demonstrated the following interrelationships: correlation between alpha and beta: $r = 0.286$, $p < 0.0001$; alpha and gamma: $r = -0.132$, $p = 0.0009$; beta and gamma: $r = 0.202$, $p < 0.0001$). In effect, this suggests that we find a positive relationship between PAI_α and PAI_β, and between PAI_β and PAI_γ, while we find a negative relationship between PAI_α and PAI_γ.

In the second analysis, the main effect of product category and interactions with the PAI scores were included in the mixed model analysis. The overall model was highly significant ($R^2 = 0.641$, $F = 19.15$, $p < 0.0001$). As shown in **Table 2**, only the category*PAI interactions were significantly related to subsequent WTP. Notably, when category was included in the analysis, PAI_β showed neither a significant main effect or interaction with category, while PAI_γ showed both a main effect and interaction effect with category. Looking further into this interaction effect, we find that PAI_γ is significantly positively related to logWTP for bags ($t = 2.38$, $p = 0.018$) and shoes ($t = 1.66$, $p = 0.845$), and that for FMCG there is a significant negative relationship ($t = -2.80$, $p = 0.006$), while clothing did not show a significant relationship ($t = -0.19$, $p = 0.845$).

A control analysis was run to test the added value of neuroimaging data on product category in explaining WTP. We first ran a mixed model with product category alone, which yielded a significant model ($R^2 = 0.452$, $F = 79.04$, $p < 0.0001$). We then included the full model with EEG scores but without interaction effects, and found that the overall explanatory value of the model increased ($R^2 = 0.641$, $F = 19.15$, $p < 0.0001$), suggesting that the addition of EEG provided an increase in explanatory power of WTP. To test whether neuroscience data provided a significantly improved explanatory power, we ran a Chow F-test (Chow, 1960) on the pseudo-R values, which yielded a significant result ($F = 1.73$, $p = 0.0464$), suggesting that there was a significant additional explanatory value of adding the EEG data to the model.

TABLE 1 | Main effects of laterality on WTP.

Term	Estimate	Std Error	DFDen	T	p
Intercept	6.052	0.166		36.55	<0.0001*
logALPHA	−0.108	0.083	172.9	−1.31	0.1914
logBETA	0.161	0.096568	281.7	1.67	0.0967
logGAMMA	0.165	0.05665	158.1	2.92	0.0038*

Independent relationship between each PAI measure and subsequent WTP for products. Asterisk denotes significant effects at p < 0.01.

Our final analysis tested whether the relationship between prefrontal asymmetry and WTP would be modulated over time. Our mixed model analysis testing the interaction between time and PAI scores for each frequency demonstrated a significant explanatory effect ($R^2 = 0.299$, $p < 0.0001$) with significant interaction effects only for the gamma frequency (PAI_γ, see **Table 3**). As shown in **Figure 4**, the relationship between PAI_γ and WTP was higher for longer stimulus durations, i.e., the closer subjects were to making the actual decision. To test whether the relationship between PAI_γ and WTP was significant already at stimulus onset, we ran a *post-hoc* mixed model analysis with WTP as the dependent variable, and with PAIγ during the first second as the independent variable and with subject as random factor. This showed that even during the first second of product viewing, PAI_γ was significantly related to WTP ($R^2 = 0.309$, $F = 41.2$, $p < 0.001$). This explanatory value was better than 2 s into product viewing ($R^2 = 0.292$, $F =9 5.2$, $p < 0.001$), but less than the third second of product viewing ($R^2 = 0.315$, $F = 390.5$, $p < 0.001$).

DISCUSSION

In this study, we have found that brain responses during product viewing are significantly related to the variation in consumers' subsequent willingness to pay for the same products. At the time that subjects viewed products, measurements of prefrontal asymmetry in brain activation accounted for 27.5% of the variation in subsequent WTP. Taking product category, which explained ∼45% of the variation in WTP, into account, improved the model's explanatory value to 64.1% of the variation in WTP.

These results provide novel insights into the basic psychological processes underlying WTP calculations and consumer choice. First, we find that WTP is mainly explained by prefrontal asymmetry in the gamma frequency band, and tentatively in the beta band. Second, prefrontal asymmetry in the gamma oscillation band showed an improved explanatory relationship with WTP responses the closer a subject is to making the actual decision, yet the model is still significant during the first second of product viewing. Both these effects have significant implications for our understanding of the

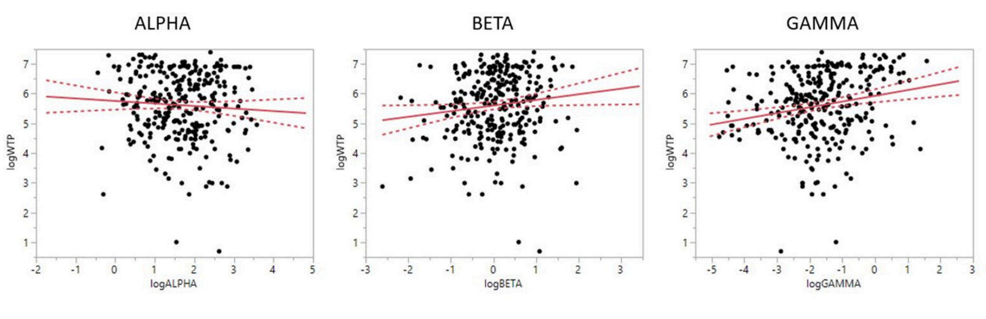

FIGURE 3 | Prefrontal laterality for alpha, beta, and gamma frequencies and WTP. Relationship between prefrontal laterality and WTP. While the alpha laterality index showed no significant relationship to WTP, gamma (and a trend for beta) demonstrated a positive relationship. Negative numbers on the laterality index (x-axis) indicate stronger right than left engagement. Please note that the higher alpha frequency band activation is inversely related to the active engagement of a brain region. Solid line indicates mean value, dotted line indicates 95% CI.

TABLE 2 | Effects of interaction between frequency band and product category.

Source	DF	DFDen	*F*	*p*
PAIα	1	176.2	0.8164	0.3670
PAIβ	1	267.4	0.7128	0.3993
PAIγ	1	172.1	12.2084	0.0006*
Category* PAI_{α}	3	262.4	0.5146	0.6726
Category* PAI_{β}	3	260.8	1.2099	0.3065
Category* PAI_{γ}	3	258.3	4.3411	0.0052*
Category	3	260.6	77.5436	<0.0001*

Interaction effects (denoted by asterisk) between PAI measures and category, showing that prefrontal asymmetry in the all ranges interacts with product category.

TABLE 3 | Effects of interaction between frequency band and time.

Source	DF	DFDen	*F*	*p*
PAIα	1	53160	34.2827	<0.0001*
PAIβ	1	53163	104.5560	<0.0001*
PAIγ	1	53166	222.1251	<0.0001*
PAIα*Time	1	53151	1.8140	0.1780
PAIβ*Time	1	53151	0.4596	0.4978
PAIγ*Time	1	53152	26.1636	<0.0001*
Time	1	53152	20.2815	<0.0001*

Interaction effects (denoted by asterisk) between PAI measures and time, showing that prefrontal asymmetry in the gamma range, but neither alpha or beta, interacts specifically with time.

psychological mechanisms underlying WTP, and will be discussed accordingly in the following paragraphs. Finally, we discuss the extent to which these EEG measures of brain activation can be used as predictive value of consumer choice as scalable, commercial applications.

Before any further discussion of the results, three issues should be noted. First, this study had a sample size of only 16 participants, a relatively small sample, in which the power of the statistics is relatively low. Further replication is needed to ensure the replicability and external validity of this study.

Second, the current study only tested women, as part of a larger study on compulsive buying behaviors in women. Although this study only tested healthy, non-compulsive consumers, the results do not yet warrant a gender-free interpretation. Thus, more studies on frontal asymmetry and consumer choice should include both women and men, and explore potential differences in asymmetric responses.

Third, in this study, we employed the Emotiv EPOC low-cost EEG system. One question could be raised about potentially lower data quality of this headset. To this end, we show that the signal quality is acceptable for the purpose of this study. This corresponds with prior studies demonstrating that this headset produces acceptable data quality and that it reproduces brain responses (both event-related potentials and frequency based responses) comparable to what has been found in studies with higher-resolution systems (Badcock et al., 2013; Grummett et al., 2014; Christopher et al., 2015; Wang et al., 2015), including emotional processing (Harmon-Jones et al., 2010; Khushaba et al., 2013), and even in mobile settings (Allison et al., 2010; Debener et al., 2012). This said, further support from these findings is needed from studies using high-resolution EEG and other neuroimaging approaches.

Effects of Separate Activity Types

The present results provide novel insights into the mechanisms of prefrontal asymmetry and their relevance to consumer choice. Prefrontal EEG asymmetry, typically reported in the alpha-band range (PAI_{α}), has been related to cognitive and emotional processes (Harmon-Jones and Allen, 1998; Pizzagalli et al., 2005; Ohme et al., 2009, 2010; Ravaja et al., 2012). Our results contradict these findings by showing that there was no significant relationship between frontal asymmetry in the alpha band and WTP decisions, even when this frequency was studied in isolation. This finding is significant, as it may suggest a specific nuance in the way that alpha band asymmetry should be interpreted in light of particular types of decision-making, and our understanding of the neurobiological mechanisms underlying the mental calculations necessary for reaching a final decision on what to pay for a specific product.

Alpha oscillations are classically related to activation decrease or inhibition of neural activation, even as an "idling rhythm" of the brain (Coan and Allen, 2003; Roche, 2004; Sauseng et al., 2005; Händel et al., 2011; Smith et al., 2017; van Diepen and Mazaheri, 2017). However, recent reports have also implied a more complex functional role of the alpha band, such as divergent thinking (Benedek et al., 2011), tonic alertness (Sadaghiani et al., 2010), and mirror neuron function (Oberman et al., 2005). Notably, Sabate et al. (2012) reported a dual nature of alpha oscillations with respect to attention, in that alpha was both related to attentional boosting of selected task calculations while decreasing the computation of other potentially interfering tasks. In the present context of prefrontal asymmetry, prior studies have linked changes in prefrontal alpha band asymmetry to approach behaviors, including reward expectancy and decision making (Miller and Tomarken, 2001), and individual traits such as reward sensitivity (Pizzagalli et al., 2005) and obesity (Ochner et al., 2009). Taken together, this suggests that the change in PAI_{α} may be related to multiple roles throughout the period of product viewing, including approach behavior and attentional gating, but not necessarily something that is crucial for making value-based decisions that manifest as WTP decisions. Notably, as PAI_{α} was not affected by product viewing time, it is possible that frontal asymmetry in the alpha frequency band is not involved in the calculations of here-and-now calculations of product value, neither at the immediate evaluation level, or during choice execution. Our findings thus challenges and nuances research on frontal alpha asymmetry and approach behavior by demonstrating that it is not related to particular choice behaviors, and by suggesting that further studies are needed to delineate the link between the neurobiology of approach behavior and consumer choice.

A novel finding was that prefrontal asymmetry in the gamma range, and tentatively in the beta range, was significantly related to WTP choices. Prefrontal asymmetry in the beta range (PAI_{β})

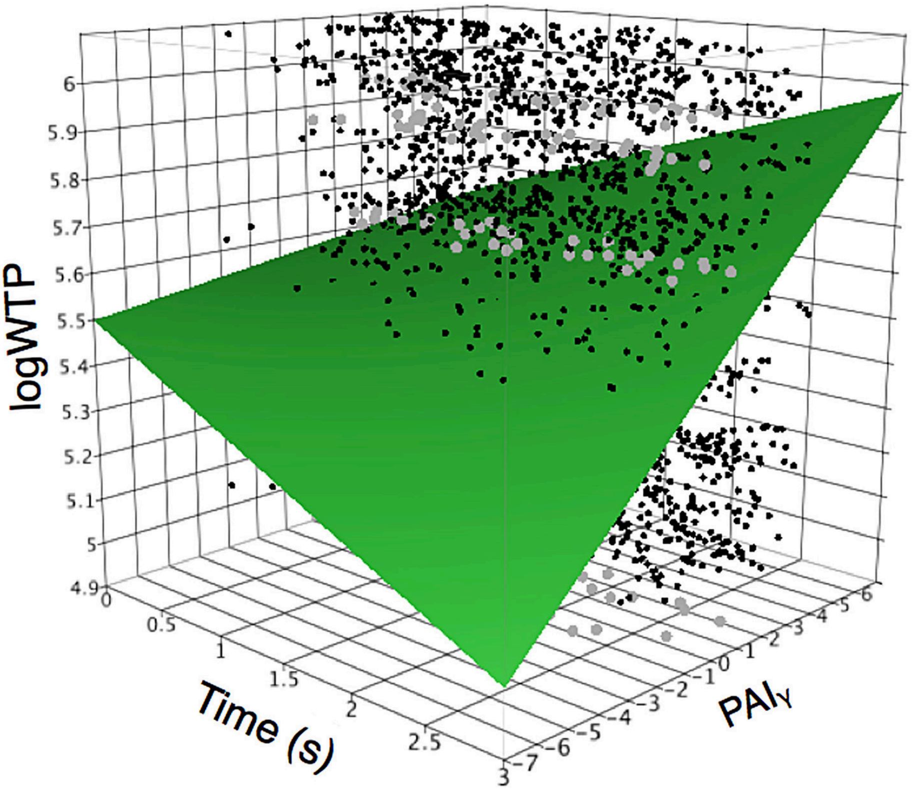

FIGURE 4 | Interactions between time and gamma on relationship to WTP. Relationship between prefrontal gamma laterality (PAI_γ) and time demonstrates that the laterality effect is strongest at the end of product viewing time, and smallest during the first period of product viewing. The plot shows the interrelationship between time from stimulus onset, PAI_γ, and logWTP, and how the relationship between PAI_γ and logWTP changes with time. In particular, note that at the time of stimulus onset (time is low) the PAI_γ is only weakly positively related to logWTP, while at higher time score (stimulus has been displayed for longer time, and the participant is closer to making a choice) the relationship between PAI_γ and logWTP is dramatically more positive. Dots denote actual data points, where black dots represent single data points, and gray dots represent multiple converging data points.

was only trend significant and thus brings a low explanatory value in relating to WTP, yet provides interesting and significant trends that should be explored further. To our knowledge, this is also the first demonstration of in PAI_β in value-based decision-making. Previous studies have demonstrated a link between beta frequency and subjective preference, such as Boksem and Smidts (2015), in which frontal beta during movie trailers were found to be significantly correlated with subsequent individual preference judgments. However, here, as in other studies of beta and choice (Polanía et al., 2014; Chand et al., 2016; Jo et al., 2016), no frontal beta asymmetry was reported, and was not part of the aims of the study. In this study, PAI_β demonstrated a negative relationship with WTP. This suggests that stronger left vs. right prefrontal asymmetry is related to a lower subsequent willingness to pay for a product. Despite the relative small size of this effect, this finding is unexpected and warrants further studies. Beta band activation in general has been linked to somatosensory and somatomotor functions (Cebolla et al., 2009; Ritter et al., 2009), language processing (Spironelli and Angrilli, 2010; Wang et al., 2012; Weiss and Mueller, 2012), and in complex decision-making and every-day behavior (Davis et al., 2011). Notably, beta oscillations have recently been implicated in perceptual decision making. For example, by using local field potential EEG in monkeys while they performed a comparison decision task, Haegens et al. (2011) found that beta oscillations during a evaluation and comparison phase were related to subsequent choice behavior. This may suggest a role for beta oscillations in comparing choice options, and that prefrontal asymmetries in this frequency band are related to value-based consumer choices. However, the observed effects in our own data showed unexpected features such as an inverse prefrontal asymmetry effect and no effect of viewing time. Interestingly, PAI_β did not change with higher proximity to the choice execution. This is at odds with recent studies that have linked beta to the decision to move (Jo et al., 2016). Also, a recent study by Boksem and Smidts (2015) showed that general beta synchrony was predictive of consumer preference and subsequent choice, suggesting a general frontal beta engagement in consumer choice. However, such research has pointed to beta being more related to a meta-cognitive aspect of decision-making (Chand et al., 2016), and for frontal theta, see Wokke et al. (2017). As the aim of the present study was to study the asymmetric frontal engagement of the brain, it is not an appropriate model for studying general beta-related activity related to the time of choice. Consequently, more studies are needed to understand the function of prefrontal beta oscillations with respect to consumer choice.

A substantial prefrontal asymmetry effect was found in the gamma oscillation band (PAI_{γ}). Gamma synchrony is thought to represent a specific kind of activation, and is believed to play an important role in the synchronization within functional units, integrating proximate or distant functional units, and can do so in a time-locked or phase-locked manner (Başar et al., 1999). Gamma activation has been shown to relate to a number of cognitive processes, including object recognition (Schadow et al., 2009; Castelhano et al., 2014; Ahlfors et al., 2015), memory types (Başar et al., 1999, 2001; Nyhus and Curran, 2010; Roux and Uhlhaas, 2014; Heusser et al., 2016; Després et al., 2017), and conscious processing (Aru and Bachmann, 2009; Doesburg et al., 2009; Luo et al., 2009; Steinmann et al., 2014; Cabral-Calderin et al., 2015; Tu et al., 2016). Most notably, gamma has been linked to the functional coupling—or binding—of brain regions that ensures integration and appropriate processing of information (Klimesch et al., 2010; Ehm et al., 2011; Schneider et al., 2011). This may suggest that the observed effects of PAI_{γ} on WTP may be related to a specific kind of value computation and possibly the link to choice execution. Notably, in a study by Ravaja et al. (2012), frontal asymmetry was found to predict consumer choice in the face of changes in price and brand provided. However, as this asymmetry was focused on alpha, we believe that our study is the first demonstration of a role for frontal asymmetric gamma oscillations in consumer choice. Moreover, as this study was for a particular type of value computation—the specific monetary valuation of products. Thus, these findings show that, besides not confirming the traditional asymmetry index in the alpha range, gamma is strongly related to consumption behavior, thus suggesting specific psychological mechanisms (for gamma and to some extent beta) in WTP calculations.

An exploratory whole-brain analysis was conducted to test for other types of EEG responses related to WTP, and the results are shown in **Table 4**.

TABLE 4 | Whole-brain analysis of alpha, beta, and gamma synchrony and WTP.

Channel/frequency	Estimate	Std. Error	df	T	p
ALPHA					
AF3	0.00004	0.00013	9,865	0.31	0.7593
AF4	−0.00035	0.00012	9,866	−2.80	**0.0051**
F3	−0.00059	0.00017	9,863	−3.54	**0.0004**
F4	0.00156	0.00029	9,867	5.46	**<0.0001**
F7	0.00025	0.00019	9,864	1.31	0.1918
F8	0.00008	0.00006	9,862	1.39	0.1635
FC5	0.00040	0.00043	9,867	0.92	0.358
FC6	−0.00020	0.00040	9,868	−0.49	0.6227
O1	0.00012	0.00066	9,867	0.18	0.8557
O2	0.00043	0.00021	9,870	2.08	**0.0373**
P7	−0.00117	0.00155	9,869	−0.76	0.4482
P8	−0.00016	0.00003	9,870	−4.58	**<0.0001**
T7	−0.00001	0.00041	9,874	−0.03	0.9731
T8	0.00001	0.00003	9,872	0.22	0.828
BETA					
AF3	−0.00003	0.00015	9,844	−0.18	0.8533
AF4	−0.00021	0.00014	9,847	−1.48	0.1383
F3	−0.00023	0.00011	9,842	−2.00	**0.0462**
F4	0.00032	0.00049	9,846	0.65	0.5159
F7	0.00027	0.00021	9,843	1.27	0.2031
F8	0.00000	0.00004	9,842	−0.03	0.9784
FC5	0.00008	0.00031	9,843	0.27	0.7897
FC6	−0.00036	0.00054	9,844	−0.66	0.5074
O1	0.00052	0.00052	9,845	0.99	0.3208
O2	−0.00107	0.00042	9,851	−2.56	0.0105
P7	−0.00458	0.00133	9,846	−3.45	**0.0006**
P8	0.00021	0.00004	9,847	5.21	<0.0001
T7	−0.00003	0.00088	9,844	−0.03	0.9745
T8	0.00019	0.00006	9,848	3.24	**0.0012**
GAMMA					
AF3	0.00125	0.00027	9,873	4.73	**<0.0001**
AF4	−0.00014	0.00024	9,866	−0.60	0.5472
F3	0.01580	0.00140	9,868	11.25	**<0.0001**
F4	−0.00191	0.00117	9,876	−1.63	0.1024
F7	0.00128	0.00046	9,865	2.81	**0.005**
F8	−0.00354	0.00129	9,868	−2.74	**0.0062**
FC5	−0.00145	0.00115	9,868	−1.25	0.2101
FC6	−0.00242	0.00082	9,868	−2.96	**0.0031**
O1	−0.04786	0.00613	9,873	−7.80	**<0.0001**
O2	−0.00329	0.00314	9,877	−1.05	0.2943
P7	0.00052	0.00282	9,867	0.19	0.8524
P8	−0.00001	0.00001	9,866	−2.47	**0.0135**
T7	−0.00005	0.00009	9,870	−0.54	0.5865
T8	−0.00049	0.00025	9,879	−1.95	0.0515

Exploratory whole-brain analysis of the relationship between frequency band power for each of the electrodes and logWTP, using a mixed model analysis. Statistical significant values with a $p < 0.05$, uncorrected, are highlighted with bold text.

Frontal Asymmetry and Product Category

Not surprisingly, since we tested products such as FMCG products and luxury goods, WTP was significantly affected by product category. However, a notable observation was that the explanatory power of frontal asymmetry in different frequency bands were affected when product category was used as a regressor in the analysis. First, asymmetry in the beta frequency was unaffected by product category, and the main effect of this frequency became insignificant (not even a trend) when product category was included as a covariate in the regression model. This suggests that asymmetry in the beta range is possibly even less important in WTP evaluations and choice, and caution should be emphasized when interpreting even the main effect for beta frequency asymmetry.

Conversely, frontal asymmetry in the gamma range was significantly influenced by product category. Bags and shoes showed a significant positive relationship to WTP, in that higher asymmetry scores (stronger left than right asymmetric engagement) were associated with a higher willingness to pay for the product. For clothing, no significant relationship was found. Interestingly, we find that the relationship between frontal gamma asymmetry and WTP was significantly negative for

FMCG products. That is, the higher the asymmetry (denoting a stronger left than right engagement) the lower the WTP.

Taken together, this suggests that emotional responses during product viewing show a product-specific relationship to what we are willing to pay for a product. With fashion items and products associated with "conspicuous consumption" (Kastanakis and Balabanis, 2014; Wang and Griskevicius, 2014), it may be less of a surprise that more positive emotional responses are related to a higher price point for the product (and thus possibly a lower price sensitivity). Conversely, for everyday FMCG products, higher asymmetry scores were related to a lower willingness to pay, suggesting that these products have a very different price sensitivity. However, as this study did not actively look for these types of responses, further research need to study these effects more specifically, as well as address the nature of the WTP-PAI relationship, and to the extent it is linear or show more complex non-linear properties. Research should also be conducted on groups who have different levels of interest for the products tested. In this study, we cannot rule out that the strong positive relationship between frontal asymmetry and WTP for bags and shoes is driven by our selection of women who were recruited for testing these types of products. Thus, additional studies on different consumer segments and varying product interests are needed.

Frontal Asymmetry and Proximity to Decision-Making

The assertion of a specific and independent role of prefrontal gamma asymmetry is further corroborated by our final analysis, in which we tested the interactions between PAI scores in all three frequency bands and product viewing time. Here, our data showed that the relationship between PAI_{γ} and WTP was significantly modulated by time. In particular, the closer to the actual decision, the stronger the relationship. No such effect was found for the PAI_{α} or PAI_{β}, which possibly implies a role for frontal asymmetry in the beta frequency range in more stable value calculations, and a dissociation from choice execution. This finding is closely related to recent studies demonstrating a role of the dlPFC in planning and executing the actual choice, while other regions such as the OFC and ACC are more related to the initial valuation of the choice options (Petrides and Pandya, 1999; Rolls, 2000, 2004; Plassmann et al., 2007, 2010; Rushworth et al., 2012). Future studies should seek to combine imaging techniques, such as simultaneous fMRI and EEG (Moosmann et al., 2008; Rosa et al., 2010), to reveal the specific morphological and neuropsychological nature of the different oscillations and their roles over time.

Prefrontal Asymmetry and Consumer Engagement, Motivation, and Choice

The present finding is among the first to demonstrate a significant relationship between brain activity and willingness to pay in consumer choice. Indeed, in contrast to a study on the brain basis of WTP using fMRI (Plassmann et al., 2007), our approach demonstrates the added value of EEG as an imaging modality for assessing consumer preference and choice. In addition to the insights gained from this on the basic mechanisms of consumer choice, our results also answers calls for neuroimaging measures that assess and predict of consumer response and choice (Butler, 2008; Garcia and Saad, 2008; Murphy et al., 2008; Senior and Lee, 2008; Wilson et al., 2008; Ariely and Berns, 2010; Fisher et al., 2010; Lee et al., 2017). Indeed, great strides are currently made in the application of neuroimaging tools and neuroscience insights in understanding, measuring and affecting consumer choice. As the demand for measures of subconscious emotional and cognitive responses is currently peaking, and substantially higher than other research approaches (http://www.greenbookblog.org/2017/06/27/the-top-20-most-in-demand-supplier-types-at-iiex-na-2017/) it is crucial that such measures being used are thoroughly documented, validated and applied to the relevant contexts. Here, it is likely that the indexing of prefrontal asymmetry responses may hold predictive powers of consumer choice in similar as well as other contexts. Even so, studies have recently demonstrated that even in a relatively small sample, brain responses can predict not only individual choice, but even market effects, such as music hits, twitter feeds, TV ratings, and box office movie sales (Berns and Moore, 2012; Dmochowski et al., 2014; Boksem and Smidts, 2015), further supporting the idea that neuroscience can provide substantial added value to consumer research, both academically and commercially. This warrants further studies, and a few notable questions should be addressed in future research:

- What are the relationship between PAI and WTP when the duration between assessment and choice is prolonged, as in when there are hours, days, and even weeks and months between the PAI assessment and consumer choice?
- What is the relationship between frontal asymmetry in different frequency bands (alpha, beta, gamma), and how do they relate to different types of value based decision-making?
- Which brain structures are most involved in the separate effects found for prefrontal alpha, beta, and gamma oscillations? Do they represent separate mechanisms of choice in, brain regions such as the OFC, dlPFC, and ACC?
- Does the effect of time on PAI_{γ} indicate separate neural mechanisms, such as OFC during the early face and dlPFC during the late phase? Is the PAI_{γ} a carrier of information from the product evaluation point to the choice execution?
- What is the temporal unfolding of frontal asymmetry, as measured by other types of EEG analyses, such as Event-Related Potentials (ERPs)?
- What is the predictive value of frontal asymmetry on larger market effects? Is frontal asymmetry more related to individual choice, or does it also signify coherent human responses at a cultural level?

ETHICS STATEMENT

This study was carried out in accordance with the recommendations of the Copenhagen Ethics Committee with written informed consent from all subjects. All subjects gave written informed consent in accordance with the Declaration of Helsinki. The study was approved under the ethical protocol KF 01–131/03, issued by the local ethics committee.

AUTHOR CONTRIBUTIONS

TR was the PI and worked on study design, project management, data preprocessing, data analysis, and was main responsible for the manuscript; MS worked on the study design and results interpretation, and on manuscript writing; MC worked on data collection and data preprocessing, and contributed to the manuscript; CS worked on study design, data preprocessing and analysis, and contributed to the manuscript.

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Lie Detection Using fNIRS Monitoring of Inhibition-Related Brain Regions Discriminates Infrequent but not Frequent Liars

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Functional near-infrared spectroscopy (fNIRS) was used to test whether monitoring inhibition-related brain regions is a feasible method for detecting both infrequent liars and frequent liars. Thirty-two participants were divided into two groups: the deceptive group (liars) and the non-deceptive group (ND group, innocents). All the participants were required to undergo a simulated interrogation by a computer. The participants from the deceptive group were instructed to tell a mix of lies and truths and those of the ND group were instructed always to tell the truth. Based on the number of deceptions, the participants of the deceptive group were further divided into a infrequently deceptive group (IFD group, infrequent liars) and a frequently deceptive group (FD group, frequent liars). The infrequent liars exhibited greater neural activities than the frequent liars and the innocents in the left middle frontal gyrus (MFG) when performing the deception detection tasks. While performing deception detection tasks, infrequent liars showed significantly greater neural activation in the left MFG than the baseline, but frequent liars and innocents did not exhibit this pattern of neural activation in any area of inhibition-related brain regions. The results of individual analysis showed an acceptable accuracy of detecting infrequent liars, but an unacceptable accuracy of detecting frequent liars. These results suggest that using fNIRS monitoring of inhibition-related brain regions is feasible for detecting infrequent liars, for whom deception may be more effortful and therefore more physiologically marked, but not frequent liars.

Keywords: fNIRS, deception, detection feasibility, inhibition, middle frontal gyrus

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INTRODUCTION

Functional near-infrared spectroscopy (fNIRS) is an advanced technique which can detect the neural signals of the cortical regions of the brain (Tsuzuki and Dan, 2014). fNIRS has competitive temporal resolution and spatial resolution compared with other techniques (Zhu et al., 2015). Additionally, fNIRS costs less (Naseer and Hong, 2015; Yücel et al., 2015), and can be used in less controlled environments (Pinti et al., 2015). Recently, fNIRS has been increasingly used in assessing the neural activities in social cognition (Naseer and Hong, 2013; Naseer et al., 2014, 2016a,b), such as deception (Hu X. S. et al., 2012; Vega et al., 2016).

Deception is a cognitive process defined as intentionally suppressing the truth and producing false responses to obtain rewards or to avoid punishments (Spence et al., 2001; Ganis et al., 2009). Generally, deception has been consistently recognized as more cognitively demanding than telling the truth (Blandón-Gitlin et al., 2014; Gamer, 2014; Gawrylowicz et al., 2016), because deceiving requires more cognitive resources to process the risk or reward calculation, to execute the plans, to speculate on others' ideas, to inhibit the truth and to produce the new responses in a clever way (Sip et al., 2008; Spence et al., 2008; Christ et al., 2009; Leue et al., 2012; Ding et al., 2014). Consequently, deception often leads to greater neural responses compared to telling the truth (Sip et al., 2008; Ganis et al., 2009; Gamer, 2014), which could make deception detection feasible. Among various cognitive activities during deception, inhibiting the truth plays a central role (Verschuere et al., 2012; Debey et al., 2015). The function of inhibition is closely linked to the neural activities of the prefrontal cortex, especially related to the activities of the left middle frontal gyrus (MFG) and the bilateral inferior frontal gyrus (IFG; Jonides et al., 1998; Aron et al., 2003; Swick et al., 2008; Marchewka et al., 2012; Sip et al., 2013). Existing studies show empirical evidence that these regions involved in inhibition could be significantly activated during different kinds of deception (Browndyke et al., 2008; Ito et al., 2011; Marchewka et al., 2012; Proverbio et al., 2013). For instance, Marchewka et al. (2012) proved that significantly greater activation of the bilateral IFG could be observed whether lying about general information or about individual information than telling the truth. In addition, Ito et al. (2011) found that deceiving in response to neutral events and to emotional events were both associated with more neural activation of left MFG than telling the truth. These studies all suggest that inhibition-related brain regions are a feasible index for detecting deception.

However, less attention has been paid to how individual differences could affect the neural activation associated with the deception. One significant factor is the frequency of deception. In real life, frequent deception offers individuals more opportunities for training themselves in deceptive skills, which makes their deceiving proficient (Jiang et al., 2013). Thus, deception would become a relatively automatic and dominant response for frequent liars (Hu X. et al., 2012; Jiang et al., 2013), that is, frequent deception makes their deceiving easier. Several studies have demonstrated this phenomenon. For example, two studies indicated that frequent deception made the process of deceiving less wrong (Verschuere et al., 2011; Van Bockstaele et al., 2012). Importantly, as deception becomes easier, it is reasonable to speculate that the neural responses of deception, particularly neural activities of inhibition-related areas, would decrease. For instance, Jiang et al. (2013) showed that the neural activities of the left MFG during strategic deception were reduced in frequent liars compared to infrequent liars. This phenomenon could pose a challenge to the application of lie detection using the inhibition-related regions as an index, as it suggests that it might fail to find greater neural responses during deception compared to telling the truth for frequent liars. Also, it suggests that distinguishing the individuals who are constant liars from innocents might become harder. The effect of frequency of deception on the detection feasibility of the deception is an important issue for real world lie-detector systems.

Using brain areas involved in inhibition (the left MFG and the bilateral IFG) as the regions of interests (ROIs), we aim to ascertain whether inhibition-related regions are a feasible index for detecting both infrequent liars and frequent liars. We not only examined the effect of frequency of deception on the neural activities associated with deception by group analysis, but also investigated the effect of frequency of deception on the accuracy of detecting different liars by individual analysis. Feasible detection requires two results: (1) in the group analysis, liars showed significantly greater neural activities compared to baseline during deceiving (as the previous studies showed, baseline was often set as the task of telling the truth without any other motivation Gamer, 2014), while innocents exhibited distinct neural activity patterns when performing deception detection tasks; and (2) in the individual analysis, acceptable accuracy could be obtained in differentiating the liars from innocents. We defined acceptable accuracy as "successful differentiation between liars and innocents with at least 70% accuracy" (from one review by Gamer, 2014, the average accuracy of deception detection from several typical studies was above 70%).

This study addresses three poorly understood aspects of lie detection: it raises the issue of the limitations of using inhibition-related brain regions to detect deception, which could initially explore whether simple neural indices could be used to detect deception for various populations. It analyses the accuracy of detecting two types of deceptive individuals (frequent liars and infrequent liars). The results of the detection accuracy could reflect the feasibility of detecting deception more clearly, and also provide a basis for detecting different deceptive individuals in practical applications. It examines the feasibility of the fNIRS technique to detect different deceptive individuals.

MATERIALS AND METHODS

Participants and Protocol

Initially, 39 healthy adults participated in this study. Seven participants were excluded from further analysis because their data were missing or because they did not fully understand the experimental instructions. Finally, 32 valid participants were included (15 males and 17 females, aged 18–26, mean age 23.47 ± 2.21 years). All the participants had normal or corrected-to-normal vision, and no neurological or psychiatric diseases. Before the experiments, written, informed consent was obtained from all the participants. Our study was approved by the Ethics Committee of the School of Psychology at South China Normal University, and the methods were carried out in accordance with approved guidelines.

Our study used the paradigm of spontaneous deception, where the participants decide when and how many times to lie rather than guiding their behaviors (Chang et al., 2014; Panasiti et al., 2014), to increase the ecological validity. Self-related questions were adopted as the experimental materials, since individuals often lie more about themselves than others (Ganis et al., 2009). Moreover, self-related information is highly practiced and readily accessible (Nunez et al., 2005). Investigating self-related deception is critical for the practical application of lie detection.

Before the experiments, all the participants were asked to fill out a questionnaire which contained 64 self-related questions. They were required to answer these questions truthfully. Then, the participants were randomly assigned into the deceptive group (18 valid participants, regarded as "liars") or the non-deceptive group (ND group, 14 valid participants, regarded as "innocents"). In each group, participants were instructed to answer self-related questions under two conditions: the task condition and the baseline condition. The orders of the task and the baseline condition were counterbalanced. Before the experiment, participants were told that they would get 20 RMB for payment. In the baseline condition, participants of both groups were required to answer the self-related questions truthfully all the time. In the task condition, a simulated task of detecting deception was conducted. Before this task, the two groups were given different instructions. Participants of the deceptive group were told to imagine the following situation: they were escaped prisoners, now under interrogation because they were suspects. A computer would record their answers, and they must hide their identity by deceiving the computer. They should answer those self-related questions with some strategy in the simulated task of detecting deception. That is, they needed to mix lies and truths, rather than tell lies all the time. They could decide when to lie and when to tell the truth spontaneously. Participants were also told that the computer would judge their identities at the end of the experiment. If the computer considered them escaped prisoners, they would lose 20 RMB for punishment. Correspondingly, participants of the ND group were required to imagine a situation: They were innocents, and now they were being interrogated because they were suspected as the escaped prisoners, so they should show their identities truthfully to convince the computer that they were not the escaped prisoners. They needed to answer those self-related questions truthfully all the time during the simulated task. They were told that if the computer considered them the escaped prisoners, they would lose 20 RMB. After the experiments, the judgment given by the computer would appear. In fact, every participant would be informed that they were determined to be innocent. After the experiments, the participants of the deceptive group were further divided into infrequently deceptive group (IFD group, regarded as "infrequent liars") and frequently deceptive group (FD group, regarded as "frequent liars") based on their number of lies in the task condition. Specifically, the top 50% of participants were defined as the FD group (9 valid participants) and the other half were defined as the IFD group (9 valid participants).

Sixty-four self-related questions were used as the experimental materials, including questions on semantic information (e.g., "Are you a student at South China Normal University?") and questions on specific episodes (e.g., "Did you call your parents yesterday?"). Each condition contained 32 self-related questions—the number of questions on semantic information and on specific episodes were equal. The questions were the same for the three groups. The questions were set in a random order in each condition. In each trial, the visual fixation "+" appeared for 0.70 s to remind the participants to notice the center of the screen, then a self-related question was represented for 3.85 s. Next, a prompt was shown for 2.80 s to guide the participants to press the button. If their answers were "yes", they should press "Q"; If their answers were "no", they should press "P". Eventually, an empty screen would appear for 7.70 s. The whole trial would last 15.05 s (see **Figure 1**). The time of each stage was set to a multiple of the temporal resolution (0.07 s) of the measurement of fNIRS.

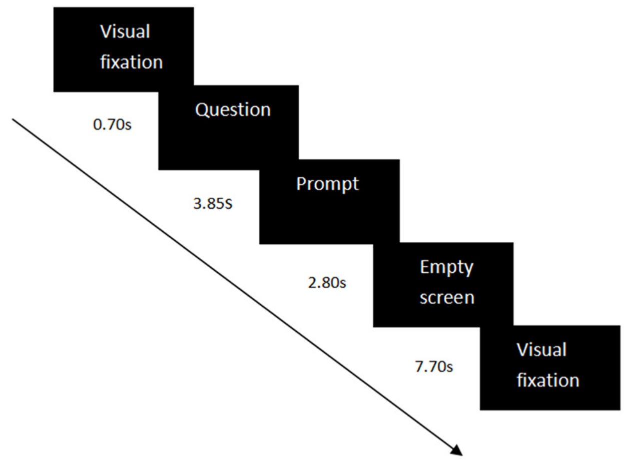

FIGURE 1 | Experiment design in each experimental trial. Each trial contained a visual fixation (0.70 s), a question (3.85 s), a prompt (2.80 s), and an empty screen (7.70 s).

Experimental Setup

Forty-two channels of an fNIRS system (FOIRE-3000, Shimadzu Corporation, Kyoto, Japan) were used in the present study (Kajimura et al., 2014). This system operates at three wavelengths (780 nm, 805 nm and 830 nm; Zhu et al., 2014). Concentration changes of oxygenated hemoglobin (HbO) and deoxygenated hemoglobin (Hb) were measured simultaneously, and changes of total hemoglobin (HbT) were calculated by adding HbO and Hb (Chang et al., 2014). Optical data were transformed into HbO and Hb according to the modified Beer-Lambert Law (Baker et al., 2014). The optode replacement and the locations of the channels are presented in **Figure 2**. According to the 10–10 system (Koessler et al., 2009), channels 8, 16, 25 and 33 were associated with the right IFG, while channels 1, 10, 18, 27 were associated with the left IFG, and channels 11, 19, 20, 28, 36 and 37 were associated with the left MFG.

Data Analysis

The data from effective experimental trials were selected as described below. Trials where the behavioral data were not recorded were excluded from further analysis. In the baseline condition of the three groups, the trials where the answers were

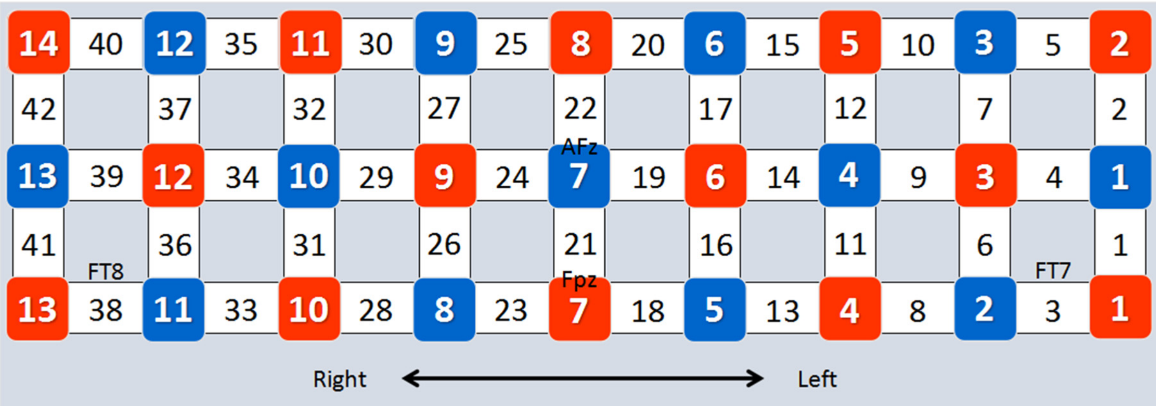

FIGURE 2 | Optode placement and channel locations. The placement of the optodes is based on the four EEG sites (FPz, AFz, FT7 and FT8) of the 10–10 system. Red squares represent emitters, blue squares represent detectors, and numbers in blank squares represent channel numbers.

not consistent with the questionnaire were excluded. In the task condition of the IFD group and the FD group, the trials where the answers were consistent with the questionnaire were excluded. In the task condition of the ND group, the trials where the answers were not consistent with the questionnaire were excluded. The remaining trials contained the truth-telling trials in the baseline condition of the three groups, the lying trials in the task condition of the IFD group and the FD group, and the truth-telling trials in the task condition of the ND group. Thus the baseline data were from truthful statements of the baseline conditions in the three groups, contrasted against task data from truthful statements of the task condition in the ND group and lies in two deceptive groups.

When processing the fNIRS data, group analysis and individual analysis were both used. These analysis were completed by NIRS-SPM (Ye et al., 2009) and SPSS 19.0. The HbO data and the Hb data were both analyzed. However, if the results of HbO analysis and Hb analysis were different, we prioritized HbO results because HbO signals are the most sensitive index to reflect cerebral blood flow activities, whereas the Hb signals are relatively noisy and unreliable (Ding et al., 2014).

Before group analysis, general linear model (GLM) analysis was performed for each participant. In GLM, observed data, such as hemodynamic response in a channel (dependent variable), are defined as a linear combination of predictor variables (independent variables) plus an error term (The formulation is $y_i = \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_j X_{ij} + \varepsilon_i$, where y_i represents observation i, X_{ij} represents value i for predictor variable j, β_i represents parameter estimated for predictor variable j, ε_i represents error for observation i.) (Suryakumar et al., 2007; Jang et al., 2009). GLM is generally used in fMRI studies (Friston et al., 1994). In this study, GLM can describe a measurement of change in HbO/Hb in terms of a linear combination of two predictor variables (the task condition and the baseline condition), so the beta values can be explained as the relationship between change in HbO/Hb and specific experimental tasks. In fact, beta values of the GLM for different conditions can be extracted as weights to account for the brain activity. The GLM analysis was performed as the following two steps: first, for each participant, the hemodynamic response function (HRF) filter and a wavelet-MDL (minimum description length) detrending algorithm were used to remove physical noise and artifacts, and a baseline correction was executed. Wavelet-MDL (minimum description length) detrending algorithm was utilized to decompose fNIRS measurements into global trends (including subject movement, blood pressure variation and/or instrumental instability), hemodynamic signals and uncorrelated noise components on distinct scales (Jang et al., 2009). After the wavelet-MDL based detrending, the average HbO time series were estimated by integrating each HRF with the relevant experimental paradigms. This method could improve the signal-to-noise ratio, and output more specific activation signals than a traditional method such as simple filtering (Jang et al., 2009; Zhu et al., 2015). Second, all the data points within 15.05 s from each effective trial in the task condition and the baseline condition were used to estimate the beta values of GLM for each participant. The mean baseline length of each participant was 458.08 s (mean 30.44 trials).

Group analysis was then conducted after GLM analysis: (1) based on the beta values, HbO and Hb maps of mean values were depicted (Matlab codes are shown in Supplementary Data Sheet 1). (2) ROIs of the brain were selected based on the HbO and Hb maps. Because inhibition function during deception was our central focus, only the obviously activated channels of the left MFG or the bilateral IFG were the candidates for ROIs. For HbO maps, obvious activation was a beta value >0.018, while for Hb maps, obvious activation was a beta value <−0.01. (3) A three-way repeated measures analysis of variance (ANOVA) test (ROI * group * condition) was conducted to examine the differences in beta values in two conditions among three groups (if there was only one ROI, a two-way ANOVA of group * condition was performed). Time course waveform analysis was performed according to the following steps: (1) the data after baseline correction were transformed to a Z-score representation. (2) For each participant, all effective trials of the task condition and all effective trials of the baseline condition were separately averaged in each channel. (3) For each group, the data of the task condition and the baseline condition were separately averaged across corresponding participants. Thus, the mean time course waveform of each channel for each condition in each group was derived (Matlab codes are shown in Supplementary Data Sheet 1). Only the data of ROIs that showed significant results in the ANOVA analysis are considered in the time course waveform analysis.

The individual analysis was performed as follows: first, detection regions were selected based on the group analysis. Secondly, receiver operating characteristic (ROC) analysis and support vector machine (SVM) analysis were both conducted to detect the accuracy in differentiating infrequent liars from innocents, and in differentiating frequent liars from innocents (Sai et al., 2014). The specific methods shall be discussed later.

RESULTS

Group Analysis

HbO Data

HbO maps of "the task condition minus the baseline condition" in two deceptive groups, the task condition of "the IFD group minus the ND group" and the task condition of "the FD group minus the ND group" are all shown in **Figure 3**. Because the focus of our study was the inhibition-related brain regions, we only paid attention to the activation of the channels from the left MFG and the bilateral IFG. The candidates of ROIs should meet two conditions: the activation of "the task condition minus the baseline condition" in either deceptive group should be obvious and the task condition of "either deceptive group minus the ND group" should be obvious. As the HbO maps show, among all the channels in the bilateral IFG and the left MFG, channel 11 and channel 20 (both in the left MFG) both met the two conditions. Thus, channel 11 and channel 20 were selected as ROIs in the HbO analysis.

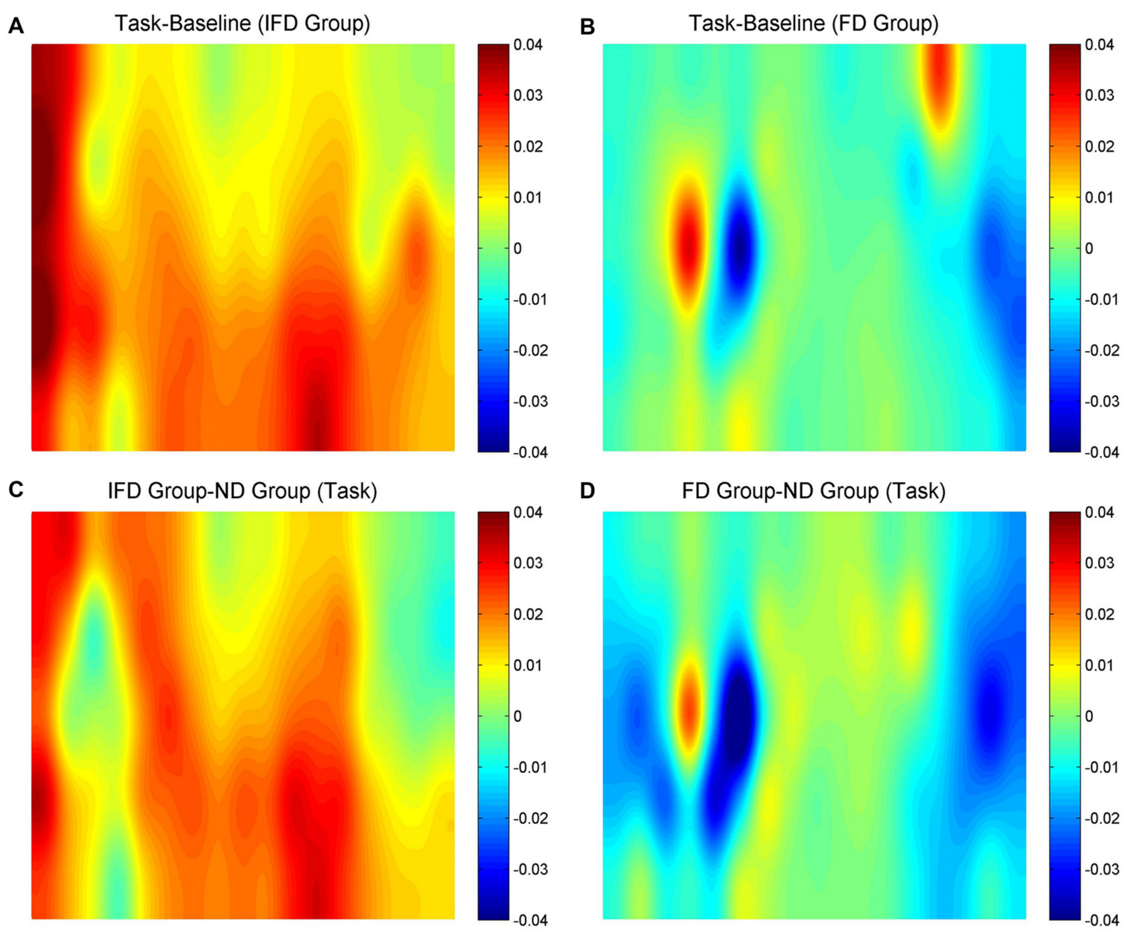

FIGURE 3 | The oxygenated hemoglobin (HbO) maps. **(A,B)** represent "the task conditions minus the baseline condition" of the IFD group and the FD group, **(C)** represents "the IFD group minus the ND group" in the task condition, and **(D)** represents "the FD group minus the ND group" in the task condition. The channel locations are the same as in **Figure 2**.

For the HbO data, we performed 2 (ROI) * 2 (condition) * 3 (group) repeated measures ANOVA. The main effect of condition was significant ($F_{(1,29)} = 5.035$, $p = 0.033$, $\eta_p^2 = 0.148$), the main effect of group was significant ($F_{(2,29)} = 4.441$, $p = 0.021$, $\eta_p^2 = 0.234$), and the interaction effect of condition and group was significant ($F_{(2,29)} = 7.153$, $p = 0.003$, $\eta_p^2 = 0.330$). Simple effect analysis indicated that, when performing the task condition, the IFD group exhibited a significantly greater increase in HbO than both the FD group ($p = 0.005$) and the ND group ($p = 0.012$). In addition, in the IFD group, the task condition led to a significantly greater increase in HbO than the baseline condition ($p = 0.0002$). However, in the FD group and the ND group, differences in changes in HbO of the task condition and the baseline condition were not significant ($p_{\min} = 0.578$). Additionally, the main effect of ROI and other interaction effects were all not significant ($p_{\min} = 0.085$; see **Figure 4**).

The data of channel 11 and channel 20 were analyzed by time course waveform analysis (**Figure 5**). Considering different hemodynamic responses owing to task preparations of the task condition and the baseline condition (Jamadar et al., 2010; Ito et al., 2012), the HbO waveforms of these two conditions were both set to start from zero on the y axis (see Supplementary Data Sheet 2,3). In channel 20, under the task condition of the IFD group, obvious HbO growth was observed approximately from 4.5 s to 7 s (the period of executing deceptive behavior). Also, during the same period, this HbO signal was greater than the baseline condition of the IFD group, as well as greater than the task conditions of FD group and ND group. However, this pattern was not observed in channel 11.

Additionally, a 2 (ROI) * 3 (group) ANOVA was conducted to examine the error differences estimated by GLM among three groups. Results showed that the main effect of group and the interaction effect of ROI and group were not significant ($p = 0.183, 0.924$), which indicated that there was no significant error differences among three groups. We also checked mean Z-scores of the HbO data in channel 11 and channel 20 from each trial. We found that no data point was out of three standard deviations above the mean ($|Z|_{\max} = 2.83$), indicating that there were no extreme values in IFD group and FD group. In summary, group differences are unlikely to be an artifact of systematic differences in noise.

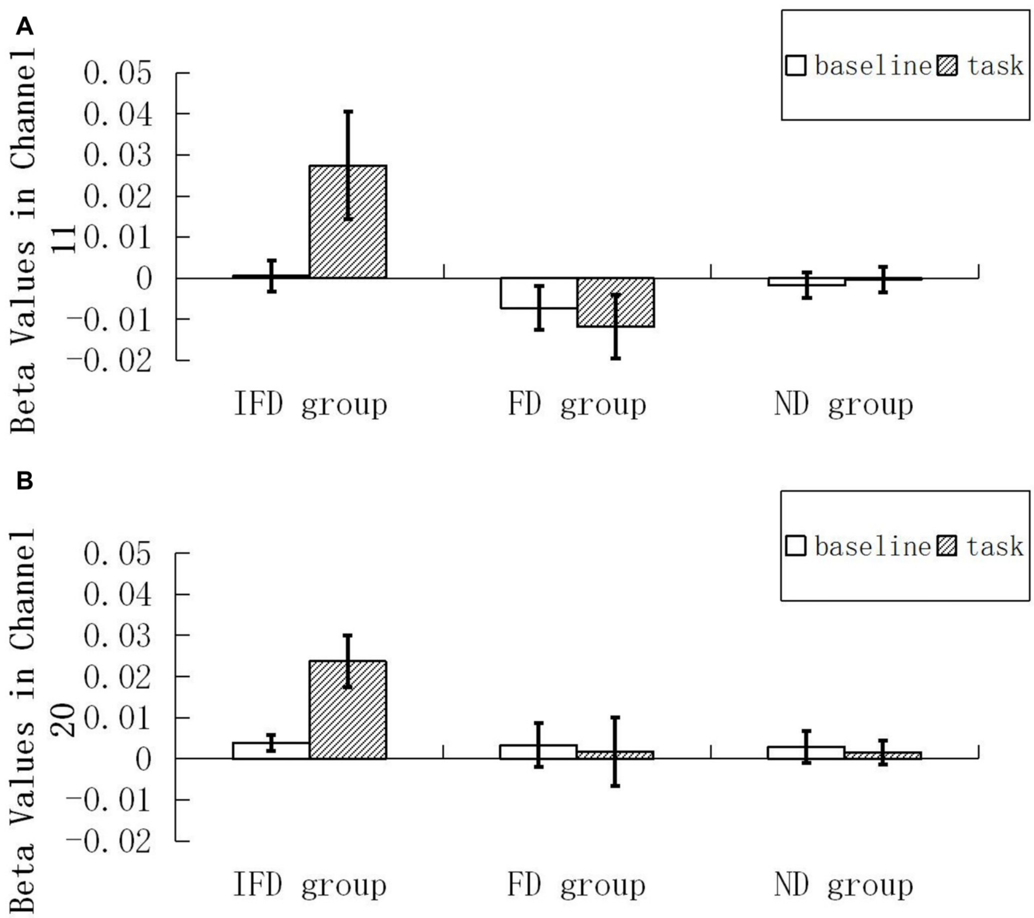

FIGURE 4 | Beta values of HbO. Mean beta value of the baseline condition and the task condition among the IFD group, the FD group and the ND group. **(A,B)** represent beta values in channel 11 and channel 20.

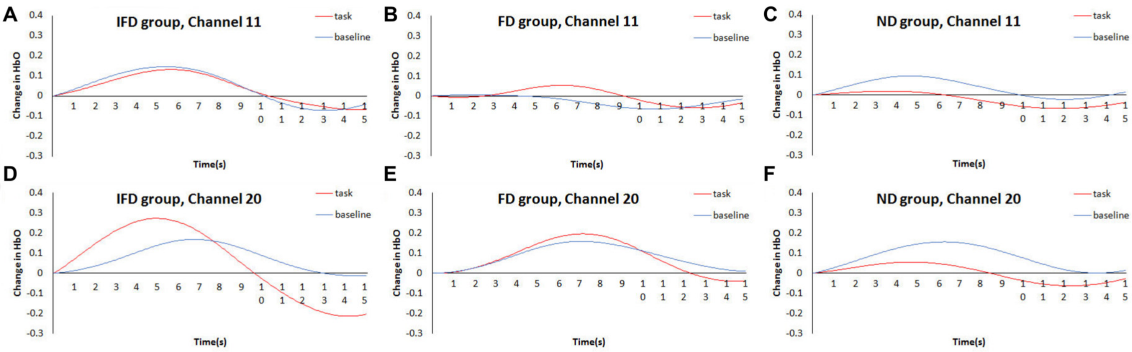

FIGURE 5 | Time courses waveform of HbO changes. The time courses of the mean HbO changes (*Z* value) of the task condition and the control condition of three groups. **(A–C)** represent HbO changes of IFD group, FD group and ND group in channel 11, **(D–F)** represent HbO changes of IFD group, FD group and ND group in channel 20.

Hb Data

Hb maps of "the task condition minus the baseline condition" in two deceptive groups, the task condition of "the IFD group minus the ND group" and the task condition of "the FD group minus the ND group" are all shown in **Figure 6**. The standards of selecting ROIs were the same as for HbO analysis. As the Hb maps show, among all the channels in the bilateral IFG and the left MFG, the activation of channel 27 was obvious in "the task condition minus the baseline condition" of the FD group, as well as in the task condition of "the FD group minus the ND group". Thus, we selected channel 27 as the only ROI in the Hb analysis.

For the Hb data, we performed a repeated measures 2 (condition) * 3 (group) ANOVA in channel 27. Results showed that the main effect of the condition, the main effect of the group, and the interaction effect of condition and group were all not significant ($p_{\min} = 0.409$). Because this channel did not show significant results, we do not present the time course waveform analysis. Also, we did not include Hb data in individual analysis.

Individual Analysis

According to the group analysis, neural activities of deception were significantly greater than the baseline from HbO data in the MFG. In two ROIs, only the data of channel 20 met the standards of differentiating liars from innocents in time course waveform analysis. Thus we selected channel 20 as the detection region.

ROC Analysis

Initially, we calculated the values of change in HbO from "the task condition minus the baseline condition" of the three groups in channel 20. These data were set as the index to discriminate between infrequent liars and innocents, as well as between frequent liars and innocents. The ROC curves are shown in **Figure 7**.

ROC analysis indicated fNIRS data could differentiate infrequent liars from innocents at 83.3% accuracy ($AUC = 0.833$ (0.633–1.000), $p = 0.008$). However, it could not differentiate between frequent liars and innocents above a chance level ($AUC = 0.484$ (0.209–0.759), $p = 0.900$).

Support Vector Machine (SVM) Analysis

Support Vector Machine (SVM) analysis was performed by the following steps: the beta values of the task condition and the baseline condition in channel 20 were both included in a SVM algorithm to build a classifier between liars and innocents. Nine participants of IFD group and 14 participants of ND group were set as Sample 1 to differentiate between infrequent liars and innocents, and nine participants of FD group and 14 participants of ND group were set as Sample 2 to differentiate between frequent liars and innocents. Sixteen participants were randomly selected for training and the left seven participants for predicting in both samples. This program was repeated 1000 times for cross validation.

Results showed that, when channel 20 was set as the detection index, the accuracy of differentiating infrequent liars from innocents was 78%. Specially, the sensitivity of deception detection was 66.67% and the specificity was 88.37%. The accuracy of differentiating frequent liars from innocents was 69.86%. The sensitivity of deception detection was 50% and the specificity was 85.3%.

DISCUSSION

The feasibility of fNIRS monitoring of inhibition-related brain regions to detect both infrequent liars and frequent liars was considered. We compared the strength of the neural activities of these two types of deceptive individuals at the group level, then analyzed the accuracy of detecting deception at the individual level.

Our study found that frequency of deception could affect the inhibition-related brain responses to deception from group analysis. Specifically, we found that during deceiving, frequent liars showed less hemodynamic activation than infrequent liars in the left MFG. This result was consistent with Jiang et al.'s (2013) study. For the infrequent liars, deception is not a dominant response, so they require greater cognitive effort to inhibit the habitual truthful response. We observed that, from the results of time course waveform analysis, infrequent liars showed an HbO

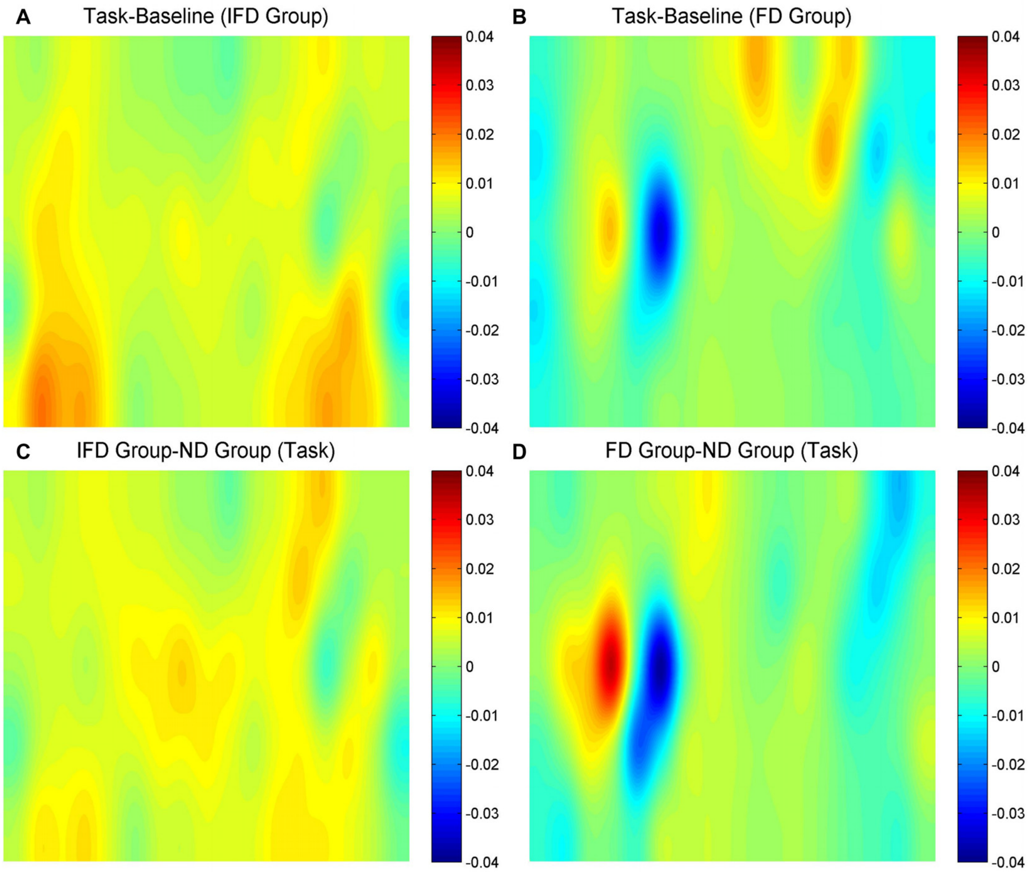

FIGURE 6 | The Hb maps. **(A,B)** represent "the task conditions minus the baseline condition" of the IFD group and of the FD group, **(C)** represents "the IFD group minus the ND group" in the task condition, and **(D)** represents "the FD group minus the ND group" in the task condition. The channel locations are the same as in **Figure 2**.

response reaching a peak at about 5 s while deceiving, within the stage of producing deceptive answers. This phenomenon suggests that the process of inhibition occurs during the stage of deceiving execution rather than the preparation stage. In addition, previous studies suggests that frequent deception makes deceiving easier (Verschuere et al., 2011; Van Bockstaele et al., 2012). Since it is their habitual response, frequent liars do not require as much cognitive effort to inhibit the truth as

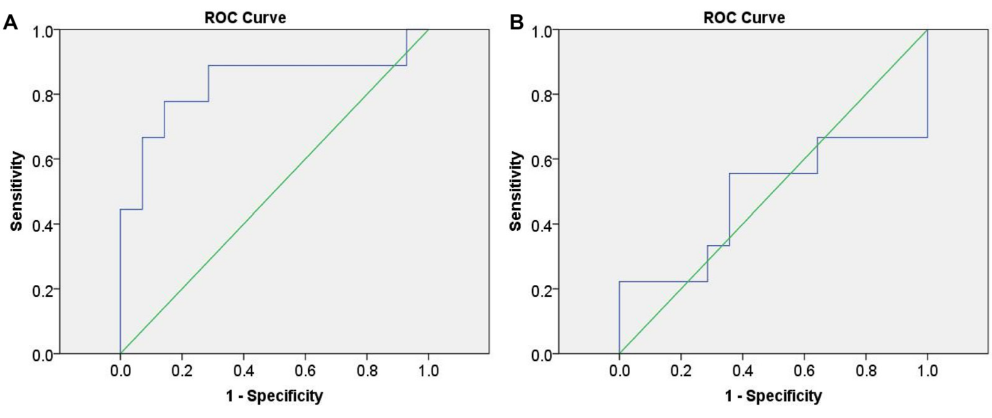

FIGURE 7 | Receiver operating characteristic (ROC) curves based on functional near-infrared spectroscopy (fNIRS) data. **(A)** represents differentiating infrequent liars from innocents and **(B)** represents differentiating frequent liars from innocents.

infrequent liars. In fact, inhibition-related brain regions are the domain-general areas whose functions would be modulated by individual variability to a large extent. Several past studies have confirmed this phenomenon. For instance, Marchewka et al. (2012) revealed that gender had an influence on the neural signals of the inhibition-related areas. Women would exhibit less activation in the left MFG than men when they deceived.

The results of group analysis indicated that, compared to the baseline condition, infrequent liars showed significantly greater neural activities in the left MFG during deceiving. One interesting result was that this difference did not apply to the activation in the bilateral IFG. A possible interpretation is that, IFG appears to be a special area involved in inhibition (Hampshire et al., 2010), so it might be activated when the process of inhibition were the primary cognitive activity. However, our paradigm of spontaneous deception involved multiple mental activities such as risk taking, mentalizing and inhibiting the truth (Sip et al., 2008; Spence et al., 2008; Christ et al., 2009; Leue et al., 2012; Ding et al., 2014), thus deceiving tended to activate the left MFG rather than IFG. The other interesting result was that, from the results of time course waveform analysis, the difference between lying behaviors and baseline among infrequent lairs reflected in only one channel in two ROIs. Because the effect of task preparation was not considered by time course waveform analysis, we speculate that this difference will decrease when examining simple neural activity associated with answering questions in deception detection tasks. Furthermore, frequent liars did not show any significant activation of the inhibition-related regions (involving the left MFG and the bilateral IFG) compared to the baseline. This finding implies that frequent liars not only need little energy to inhibit the truth, but also execute the deceptive response as if they are telling the truth (Blair et al., 1997). Additionally, different from many previous studies, we examined the neural activities of innocents, rather than just the liars (Jiang et al., 2013; Li et al., 2015). We found that innocents did not manifest significantly greater neural activation than baseline in any part of inhibition-related regions while performing deception detection tasks. These results illustrated that infrequent liars and innocents show distinct neural activation patterns in inhibition-related regions during the deception detection tasks, indicating that infrequent liars could be separated from innocents. However, due to similar activation patterns, frequent liars are indistinguishable from innocents.

Individual analysis indicated that frequency of deception could have an effect on the accuracy of detecting deception. For ROC analysis, our results showed that fNIRS could differentiate infrequent liars from the innocents at an accuracy with 83.3%, while it could not successfully distinguish the frequent liars from the innocents above a chance level. Moreover, SVM analysis indicated that, using the left MFG as the detection region, 78% classification accuracy, as well as 66.67% sensitivity of deception detection, could be achieved when detecting infrequent liars. However, when detecting frequent liars, classification accuracy was lower than 70%, and the sensitivity of deception detection declined significantly. Combined with ROC analysis and SVM analysis, our study indicated that above-chance accuracy could be obtained when differentiating the infrequent liars from innocents. Moreover, it suggests that the detection index has a moderate ability to distinguish between deceiving and telling the truth in infrequent liars. In contrast, when differentiating the frequent liars from innocents, acceptable accuracy could not be achieved. We could not find out the differences between lying responses and truthful responses from any frequent liar.

In practical applications, the index of inhibition-related regions should be used with great caution in detecting various liars. We propose that two possible measures could improve the ability to detect frequent liars. First behavioral analysis could be adopted as a supplementary method when using the fNIRS technique. Despite the mainstream view that the neural signal of deceiving should be more reliable (Bhutta et al., 2015), behavioral analysis combined with neural activity analysis might provide a more comprehensive view of the deception process. In fact, previous fNIRS study has verified that combined indices (fNIRS data and behavioral data) could improve the accuracy of lie detection beyond simple fNIRS index (Sai et al., 2014). Secondly, not only the regions involved in inhibition, but also regions associated with other cognitive activities during deception should be examined by fNIRS. For instance, even though frequent liars do not need much effort to inhibit the truth, they still need effort to consider their strategy of deceiving. This process is strongly linked to the function of planning (Ding et al., 2014). Planning is thought to be typically associated with the function of the superior frontal gyrus (SFG; Baker et al., 1996), so it is plausible that bringing SFG into the detection index might enhance the ability of fNIRS to detect frequent liars. Since more social cognition are engaged in interpersonal interaction (Volz et al., 2015), interrogation could be conducted more frequently by a human than by a computer in the future.

CONCLUSION

In summary, our study has indicated that using inhibition-related brain regions to detect deception is feasible for infrequent liars and not feasible for frequent liars.

AUTHOR CONTRIBUTIONS

FL and SH designed the experiment. FL analyzed and interpreted the data, and wrote the manuscript. HZ provided technical support for analyzing and interpreting the data, and helped write and revise the manuscript. SH, HZ and JX revised the manuscript. FL, JX, QG, HG, SW and XL performed laboratory work and collected the data. All the authors read and approved the final manuscript.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fnhum.2018.00071/full#supplementary-material

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The Effects of Money on Fake Rating Behavior in E-Commerce: Electrophysiological Time Course Evidence From Consumers

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Online ratings impose significant effects on the behaviors of potential customers. Thus, online merchants try to adopt strategies that affect this rating behavior, and most of these strategies are connected to money, such as the strategies of returning cash coupons if a consumer gives a five-star rating (RI strategy, an acronym for "returning" and "if") or returning cash coupons directly with no additional requirements (RN strategy, an acronym for "returning" and "no"). The current study explored whether a certain strategy (RN or RI) was more likely to give rise to false rating behaviors, as assessed by event-related potentials. A two-stimulus paradigm was used in this experiment. The first stimulus (S1) was the picture of a product with four Chinese characters that reflected the product quality (slightly defective vs. seriously defective vs. not defective), and the second stimulus (S2) displayed the coupon strategy (RN or RI). The participants were asked to decide whether or not to give a five-star rating. The behavioral results showed that the RI strategy led to a higher rate of five-star ratings than the RN strategy. For the electrophysiological time courses, the N1, N2, and LPP components were evaluated. The slightly defective products elicited a larger amplitude of the N1 component than the seriously defective and not-defective products, reflecting that perceptual difficulty was associated with the processing of the slightly defective products. The RI strategy evoked a less negative N2 and a more positive LPP than the RN strategy, indicating that the subjects perceived less conflict and experienced stronger incentives when processing the RI strategy. These findings will benefit future studies of fake online comments and provide evidence supporting the policy of forbidding the use of the RI strategy in e-commerce.

Keywords: fake rating behavior, money, N2, LPP, neuromarketing

INTRODUCTION

Online customer reviews are often thought of as electronic word of mouth (eWOM), which can help consumers simplify their search process and more easily determine product quality and fit uncertainty (Yin et al., 2014). A star rating (ranging from 1 to 5 stars) is typically included in each online review, and previous studies have noted that consumer-generated ratings have a substantial impact on the success or failure of a product in internet commerce (Chevalier and Mayzlin, 2006; Lafky, 2014). For example, it has been found that even one extra star in a Yelp review could increase revenues by 5–9% (Economist, 2015; Poddar et al., 2017). Given the great value of star ratings, online merchants have tried to adopt various marketing strategies to affect online rating behaviors, which may increase the number of false reviews.

Money has often been used as a tool in many marketing strategies, such as in the strategy of returning discount/cash coupons to consumers with no other request (RN strategy, RN is an acronym of "returning" and "no"). Some online sellers even return money or coupons directly if buyers give a five-star rating (RI strategy, RI is an acronym of "returning" and "if"), a practice that is ostensibly forbidden to be published on an online website by many e-commerce platforms (e.g., Taobao in China). However, this practice is still prevalent. For instance, the subjects in our experiment had received such incentives more than once for various mailed products. These strategies could result in false ratings. Only recently have researchers begun to analyze fraud in the context of online reviews (Hu et al., 2012; Poddar et al., 2017; Yamak et al., 2017). For example, Hu et al. (2012) proposed a statistical method for detecting false online review manipulation and assessed how consumers responded to products with manipulated reviews. Poddar et al. (2017) investigated the online rating bias that is elicited by false advertising and slander and mined big data to develop a method to measure online rating bias. These studies mainly used machine learning methods and focused on how to improve accuracy in identifying fake comments. However, from the perspective of consumer behavior, little is known about how the marketing strategies that are adopted by online merchants affect fake rating behavior in e-commerce and why online merchants adopt these illegal strategies.

The main distinction between the RI and RN strategies lies in the different forms that the monetary reward is given. Money, as a powerful social construct, can have a large impact on one's goals and behaviors. Several studies have demonstrated that money can increase the likelihood of self-interested or immoral behavior (Cullen et al., 1985; Agnew, 1994; Vohs et al., 2006; Vohs and Schooler, 2008; Kouchaki et al., 2013). In addition to the idea that money represents a reward in the feedback phase, mere exposure to money (as priming), devoid of any goal to which it might be relevant, could lead to behaviors that are relatively impersonal and self-focused (Vohs et al., 2006, 2008). The cash coupons that are used in the RI strategies are goal-related rewards that are given when the subjects performed the five-star rating behavior, whereas the cash coupons in the RN strategies are goal-unrelated rewards that are given to the subjects without any contingency. We suppose that the RI strategy decreases the evaluation process underlying rational choice and self-control and strengthens the motivation of consumers to engage in fake rating behaviors. However, there has not been direct behavioral or neurological evidence supporting this hypothesis.

To investigate how marketing strategies affect the fake rating behaviors that are observed in e-commerce in the context of an electrophysiological time course, event-related potentials (ERPs), a non-invasive brain scanning technique that measures the perceptual and cognitive processing of stimuli, were analyzed. Furthermore, the current study explored the moderating effect of product quality on the processing of different marketing strategies. This research furthers the study of online false reviewing and encourages e-commerce platforms, as well as government regulators, to realize the "darker side" of illegal online strategy manipulation.

Two ERP components have been associated with the processing of monetary rewards, namely, the N2 component and the late positive potential (LPP). N2 is a negative potential that peaks between 200 and 400 ms post-stimuli (Folstein and Van Petten, 2008; Dickter and Bartholow, 2010) and is consistently localized in the anterior cingulate cortex (ACC) (Nieuwenhuis et al., 2003; Yeung et al., 2004). There is evidence that the N2 component reflects conflict and mismatch from a visual modality (Van Veen and Carter, 2002; Folstein and Van Petten, 2008), which is sensitive to not only physical attribute conflicts but also perception conflicts (Ma et al., 2007, 2010; Han et al., 2015; Jin et al., 2017). For example, using a two-stimulus paradigm, Han et al. (2015) reported more negative N2 components when the second stimulus did not match the physical attributes of the first stimulus in terms of color or shape. In a brand extension evaluation task with pairs of stimuli, the N2 amplitude was found to be greater when the participant encountered a perceptual conflict between the brand name (S1) and the extension product name (S2) (Ma et al., 2007, 2010). In a study of immoral behaviors, Lahat et al. (2013) observed larger N2 amplitudes in response to moral violations than in response to conventional violations, and Yoder and Decety (2014) used a conflict-monitoring standpoint to explain the N2 component that is elicited by morally good and bad actions. Furthermore, researches have shown that compared with telling the truth, lying evokes greater N2 amplitudes (Wu et al., 2009; Suchotzki et al., 2015; Fu et al., 2017). The behaviors involved in giving a five-star rating to the defective products were immoral actions that were similar to deceptive behaviors, and subjects should detect a perceptual conflict, as reflected by the N2 component.

In addition to the N2 component, the LPP, as a later relevant component, occurs ∼300–800 ms post-stimulus. The LPP could be responsible for indexing later controlled processes that reflect cognitive reappraisal of stimuli, top-down cognitive control and attentional reallocation to motivationally salient stimuli (Sabatinelli et al., 2007; Dennis and Hajcak, 2009; Larson et al., 2009). In studies that have evaluated moral behavior, some researchers suggested that the LPP may be associated with conflict-resolution processing (Chiu Loke et al., 2011; Yoder and Decety, 2014; Wang et al., 2016), and moral actions were found to elicit greater LPP amplitudes than immoral actions (Yoder and Decety, 2014). Thus, the immoral action of giving a five-star rating to a defective product would evoke the LPP component. Moreover, in decision-making studies, the LPP (P3b) was found to be associated with the motivational significance of ongoing stimuli (Nieuwenhuis et al., 2005; San Martín, 2012), and the stimuli with stronger motivational impacts heightened the LPP amplitudes (Polezzi et al., 2010). The cash coupon incentives used in RI and RN strategies in exchange for providing a fake rating are different and, thus, might have different effects on the LPP component.

In the present experiment, we applied ERPs to investigate the neurophysiological processes of how the different monetary rewards used in the RI and RN strategies affect fake rating behaviors and to explore the moderating effect of product quality (slightly defective vs. seriously defective vs. not defective) on the processing of these strategies. The participants were asked whether they would give a five-star rating for different imperfect products using either the RI or RN marketing strategies. In the RI strategy, the participants would receive cash coupons only if they gave five stars to the defective products; whereas in the RN strategy, they would receive cash coupons without any additional contingencies. Thus we hypothesized that the goal-related monetary rewards used in RI strategy would alleviate the perceptual conflict of immoral action and had a stronger incentive than the goal-unrelated monetary rewards used in RN strategy, which were reflected by a less negative N2 amplitude and a larger LPP amplitude for RI in contrast to RN strategy, respectively. As a result, RI strategy might lead to a higher rate of giving five-star ratings. Meanwhile, product quality might have an impact on fake rating behavior such that a better product quality would result in a higher probability of giving five-star ratings, which might also be implicated by ERPs components. Overall, this study allowed us to explore how marketing strategies affect the immoral rating behaviors of customers at the neural level and to discover, from a customer's perspective, the reason why online sellers are willing to adopt illegal strategies.

MATERIALS AND METHODS

Participants

Twenty-one right-handed students from Ningbo University (10 females, all right-handed), aged 20–26 years (mean age $= 23 \pm 1.26$ years), participated in this experiment. Information regarding the experiment was posted on the campus BBS (bulletin board system) to recruit the participants. All participants had experience in online shopping and were familiar with online marketing strategies (e.g., RI or RN strategies), were native Chinese speakers with no history of neurological or psychiatric abnormalities, and had normal or corrected-to-normal vision. The study was approved by the Internal Review Board of the Center for Management Decision and Neuroscience at Ningbo University. Before the experiment, written informed consent regarding issues such as awareness of the experimental task and protection of personal privacy, health, safety and dignity, was obtained from all the subjects in accordance with the Declaration of Helsinki. Participants were compensated for their time after the experiment. The electroencephalography (EEG) data of two participants were discarded due to excessive recording artifacts, leaving valid data for 19 participants (9 females and 10 males) for the final EEG data analysis.

Experimental Stimuli

A two-stimulus paradigm was used in the experiment. The first stimulus (S1) consisted of a product picture with a phrase below it that described the quality of the product. The product picture depicted either a sweater or a pair of shoes from the category of clothing to control for color, style and brand. Each phrase contained four Chinese characters, and the product quality included three categories: slightly defective (e.g., a small color difference), seriously defective (e.g., serious color difference) and not defective (e.g., no chromatic difference). Each of the quality categories comprised 5 phrases. Specifically, S1 consisted of 30 product pictures with phrase information reflecting the product quality. The second stimuli (S2) comprised 8 coupon strategies that were associated with the products chosen from two strategy categories (four coupons per category), namely, the strategy of returning cash coupons if given a five-star rating (RI strategy) and returning cash coupons with no contingencies (RN strategy). The stimuli used in the experiment consisted of 240 pairs of product pictures with product quality information (S1) and coupon strategies (S2), i.e., 2 pictures (sweater or shoes) $\times$ 3 categories of quality information $\times$ 5 phrases per quality category $\times$ 2 categories of coupon strategies $\times$ 4 coupons per strategy.

Procedures

The participants sat in a comfortable chair to perform the experimental tasks in a sound-attenuated and electrically shielded room. A keypad was provided for the participants to input their choices. The stimuli were displayed in the center of a computer screen located 1 m away from the participant's eyes. The visual angle of all the stimuli was $4.58^{\circ} \times 4.58^{\circ}$. The E-prime 2.0 software package (Psychology Software Tools, Pittsburgh, PA, USA) was adopted to control the stimuli and acquire the behavioral data.

The experiment consisted of four blocks, each containing 60 pairs of stimuli. For each trial of a block, first a fixation of "+" was presented against a gray background for a random interval from 600 to 800 ms; then, S1 was presented for 2,000 ms followed by a blank screen ranging from 600 to 800 ms between S1 and S2. S2 disappeared until a response was made, followed by presentation of a blank screen for 600 to 800 ms (as shown in **Figure 1**). The participant was able to rest for several minutes after each block.

The participants were first provided the following introduction scenario: "You received a sweater or a pair of shoes from taobao.com, and you checked the quality of the product (the quality result was reflected by S1). Additionally, you found a cash coupon associated with the product given by the online sellers, which was reflected by S2. Please evaluate whether you would give a five-star rating according to the information of S1 and S2 by using the keypad." After the introduction, each subject performed 10 training trials to become familiarized with the procedure. The response-to-hand assignments were counterbalanced across all the subjects. The participants were paid 50 Chinese yuan (approximately US$7) as payment.

ERP Recording and Analysis

In this experiment, EEG data were recorded (sampling rate of 1,000 Hz) using a NeuroScan SynAmps2 Amplifier (Curry 7, Neurosoft Labs, Inc., Virginia, USA) and a cap containing 64 Ag/AgCl electrodes. The cephalic (forehead) location served as the ground, and the left mastoid served as an online reference. The vertical and horizontal electrooculograms (EOGs) were

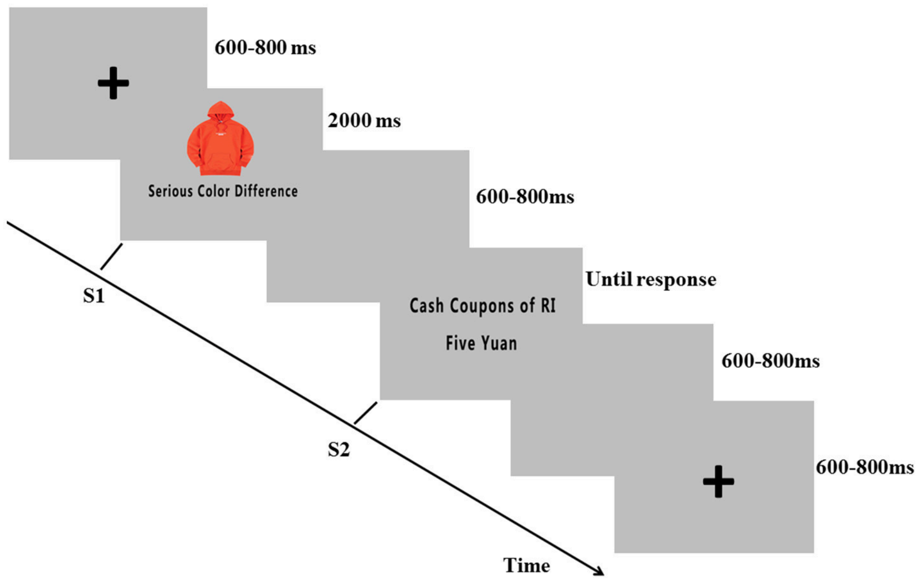

FIGURE 1 | Experimental task: The participants were instructed to evaluate whether they would give a five-star rating for the S1 for different coupon strategies (RI or RN strategies) provided in S2.

recorded with a pair of electrodes placed above and below the left eye (vertical EOG), and another pair of electrodes placed 10 mm from the lateral canthi of both eyes (horizontal EOG). The electrode impedance was maintained below 5 kΩ during the experiment.

Electroencephalogram Analysis

The NeuroScan analysis software (Scan 4.5, Neurosoft Labs, Inc., Virginia, USA) was used to process the offline EEG signals. The EEG signals were digitally filtered with a low-pass filter at 30 Hz (24 dB/Octave). Any EOG artifacts were corrected by the method proposed by Semlitsch et al. (1986) for all subjects. The EEG recordings were segmented into epochs from 200 ms before the onset of the second stimulus (S2) to 800 ms after the onset of S2, with the prestimulus period used as baseline. Any trials with electro-oculography activity or other artifacts (such as amplifier clipping, bursts of electromyographic activity or peak-to-peak deflections exceeding ±100 μV) were excluded, and more than 30 sweeps for each condition remained. The EEG recordings for each participant were averaged separately within the six conditions (3 categories of product quality×2 categories of coupon strategies).

Based on visual inspection of the grand average waveforms and the related studies mentioned in the introduction, the N1, N2, and LPP components were analyzed in our experiment. To analyze the mean amplitudes of the N1, N2, and LPP components, the time window for the N1 component was specified as 100–120 ms after the onset of S2, the N2 component as 270–370 ms, and the LPP component as 400 ms to 600 ms. According to the brain locations of the ERP components and the guidelines given by Gui et al. (2016), the nine electrodes corresponding to the coronal and sagittal factors, i.e., the F3, FZ, F4, FC3, FCz, FC4, C3, Cz, and C4 electrodes in the frontal, fronto-central and central areas, were used for N1 and N2, and the C3, Cz, C4, CP3, CPz, CP4, P3, Pz, and P4 electrodes in the central, centro-parietal and parietal areas were used for LPP. Repeated measures analyses of variance (ANOVAs) were conducted using SPSS (SPSS 16.0, SPSS, Inc., Chicago, IL) separately for the N1, N2, and LPP components. The within-subject factors consisted of the 3 categories of product quality (slightly defective vs. seriously defective vs. not defective), the 2 categories of coupon strategy (RI strategy vs. RN strategy), and the 9 electrodes. The Greenhouse–Geisser correction was used when necessary (uncorrected *df* is reported with the ε and corrected *p*-values), and the Bonferroni correction was used for multiple paired comparisons.

RESULTS

Behavioral Results

The rates that participants gave five-star ratings (FRs) and their reaction times (RTs) were analyzed separately by within-subject ANOVAs with factors of product quality (3 categories: slightly defective vs. seriously defective vs. not defective) and coupon strategy (2 categories: RI strategy vs. RN strategy). Regarding the FRs, there were significant main effects of the coupon strategy [$F_{(1, 20)} = 6.278$, $p < 0.05$, $\eta^2 = 0.239$] and product quality [$F_{(2, 40)} = 245.873$, $\varepsilon = 0.690$, $p < 0.001$, $\eta^2 = 0.925$] factors, with no interaction effect between the two factors. The FR of the RI strategy ($M = 0.561$, $S.E. = 0.025$) was higher than that of the RN strategy ($M = 0.499$, $S.E. = 0.024$). For the factor of the product quality, Bonferroni-corrected pairwise comparisons showed that the FR of the not defective products ($M = 0.960$, $S.E. = 0.015$) was larger than that of both the slightly defective products ($M = 0.570$, $S.E. = 0.050$) ($p < 0.001$) and the seriously defective products ($M = 0.061$, $S.E. = 0.015$) ($p < 0.001$). Furthermore, the FR of the slightly defective products was larger than that of the seriously defective products ($p < 0.001$). The results of the FRs are shown in **Figure 2**.

Regarding the RTs, the two-way 3 (product quality) × 2 (coupon strategy) within-subjects ANOVA showed a significant main effect of the product quality factor [$F_{(2, 40)} = 13.834$, $p < 0.001$, $\eta^2 = 0.409$], with no salient main effect of the coupon strategy factor and no interaction effect between product quality and coupon strategy. The pairwise comparison test for the product quality factor showed that the RT for the slightly defective products ($M = 757.381$, $S.E. = 71.856$) was longer than the RTs of the seriously defective products ($M = 634.908$, $S.E. = 64.777$) ($p < 0.001$) and the not defective products ($M = 603.061$, $S.E. = 51.566$) ($p < 0.01$). However, no significant difference in RT was observed between the seriously defective products and the not defective products ($p > 0.05$) (as shown in **Figure 3**).

In addition, to explore if there were gender differences with regard to the behavioral results, mixed-design ANOVAs were performed separately on FRs and RTs, including gender as a between-subject factor. However, neither the main effects of gender nor any interactions involving gender were significant ($ps > 0.05$).

EEG Results

The grand-average ERPs for the factors of the coupon strategy and product quality are shown in **Figures 4**, **5**, respectively.

A three-way 3 (quality phrase: slightly defective vs. seriously defective vs. not defective) × 2 (coupon strategy: RI strategy vs. RN strategy) × 9 (electrode) within-subjects ANOVA for N1 in the time window from 100 to 120 ms was conducted. There was a significant main effect of the product quality factor [$F_{(2, 36)} = 4.968$, $p < 0.05$, $\eta^2 = 0.216$], with no significant effect of the coupon strategy and no interaction effect between the product quality and coupon strategy factors. Bonferroni-corrected pairwise comparisons showed that the average N1 amplitude in the condition of a slightly defective product ($M = -2.420$, $S.E. = 0.353$) was marginally more negative than that in the condition of a seriously defective product ($M = -1.744$, $S.E. = 0.434$) ($p < 0.1$) and was significantly more negative than that in the condition of a not defective product ($M = -1.412$, $S.E. = 0.525$) ($p < 0.01$), with no salient difference between the seriously defective product and not defective product conditions ($p > 0.1$).

An ANOVA for the mean N2 amplitude in the 270–370 ms time window was also conducted and revealed a significant effect of the coupon strategy factor [$F_{(2, 36)} = 6.132$, $p < 0.05$, $\eta^2 = 0.254$], and the N2 amplitude elicited by the RN strategy ($M = 0.558$, $S.E. = 0.669$) was more negative than that elicited by the RI strategy ($M = 1.378$, $S.E. = 0.605$). There was no salient effect of the product quality factor and no interaction effect between the product quality and coupon strategy factors.

An ANOVA for the mean LPP amplitude in the 400–600 ms time window revealed a significant main effect of the coupon strategy factor [$F_{(2, 36)} = 4.914$, $p < 0.05$, $\eta^2 = 0.214$]. The RI strategy ($M = 3.035$, $S.E. = 0.552$) evoked a larger LPP component than the RN strategy ($M = 3.035$, $S.E. = 0.552$). There

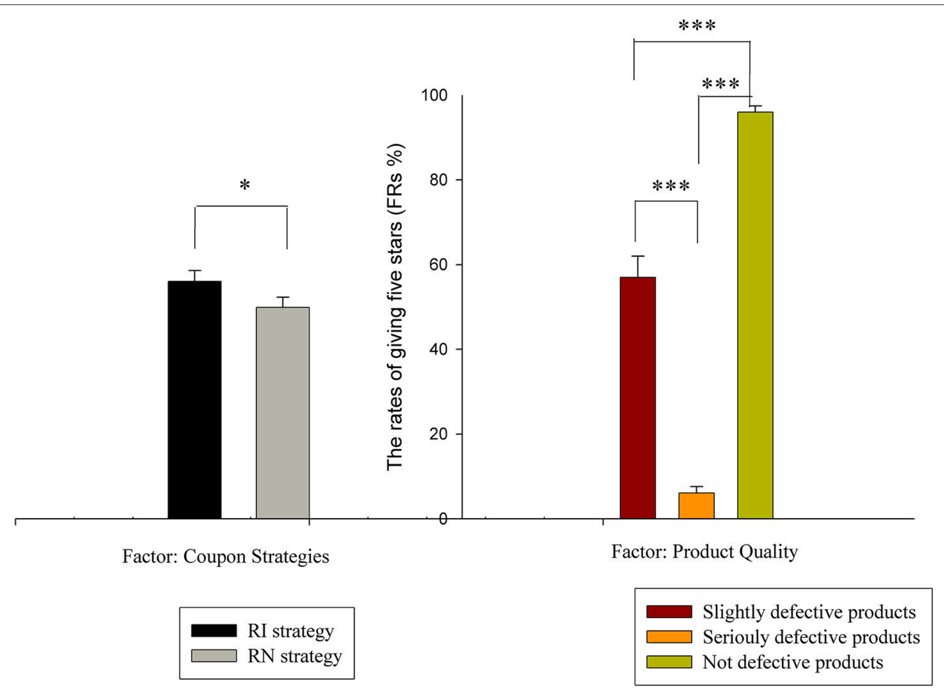

FIGURE 2 | FR results. The rates of giving five-stars for the factors of coupon strategy (RI vs. RN) and product quality (slightly defective products vs. seriously defective products vs. not defective products). *$p < 0.05$, ***$p < 0.001$.

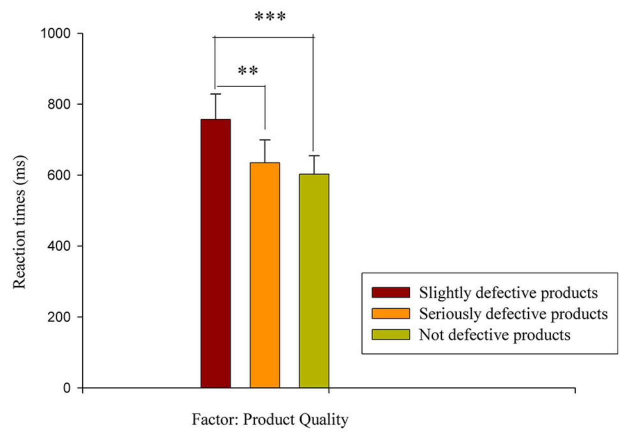

FIGURE 3 | RT results. The reaction times for the product quality factor (slightly defective products vs. seriously defective products vs. not defective products). $^{**}p < 0.01$, $^{***}p < 0.001$.

was no significant main effect of the product quality factor, and furthermore, no interaction effect was found between the product quality and coupon strategy factors.

To investigate if there were gender differences in the EEG results, mixed-design ANOVAs that included gender as a between-subject factor were performed separately for the N1, N2, and LPP amplitudes. However, in line with the behavioral results, there were no main effects of gender or any interaction effects involving gender for any of the ERP components ($ps > 0.05$).

DISCUSSION

Researchers have recently expressed increasing interest in employing neuroscientific tools to investigate the neural basis of marketing phenomena. For example, several studies have used ERPs to explore the neural basis of brand extension in order to determine a strategy to enhance the success of brand extension (Ma et al., 2007, 2010; Shang et al., 2017). In the present study, we investigated both how coupon strategies affect the fake rating behaviors of online customers and the temporal dynamics of the neural activity that are associated with different marketing strategies. These findings helped us to further understand why online platforms forbid certain strategies, such as money being returned if a customer provides a five-star rating, at the neurological level. Additionally, the moderating effect of the product quality received from online shopping was considered in this study.

Behaviorally, a remarkable FR effect was found based on the coupon strategy (i.e., customers were more willing to give a five-star rating with the RI strategy compared to the RN strategy). According to the Tool Theory of money motivation, monetary incentives have effects on behavioral performance, which result not only from the monetary rewards in the feedback stage but also from thinking about money, even unconsciously through priming (Lea and Webley, 2006; Vohs et al., 2006; Zhou et al., 2009; Ma et al., 2015). However, different forms of giving monetary rewards were found to have different levels of attractiveness. In our experiment, the RI strategy had a stronger effect on rating behaviors than the RN strategy. That is, compared with giving cash coupons without any contingencies, people tended to give more five-star ratings when the decision led to a monetary reward. Thus, the strategy that involved returning cash coupons as monetary rewards if a five-star rating was given increased the falsity of the review comments to a greater extent than other strategies. Additionally, the FR was inversely related to the quality of the products received from the online platform. That is, products with higher quality are more likely to receive a five-star rating by consumers. However, the product quality had no moderating effect on the validity of the coupon strategy. Thus, regardless of the product quality, the RI strategy would induce greater falsity of the rating comments than the RN strategy.

In terms of RTs, a significant effect was found for the product quality factor; slightly defective products corresponded to longer RTs than not defective and seriously defective products, with no difference in RT between the latter two. Previous studies have found that the task difficulty affects RT, with more difficult tasks requiring more time to process (Ma et al., 2014; Dunn et al., 2017). It was relatively easier for the participants to decide whether to give a five-star rating in the not defective product and seriously defective product conditions. In terms of

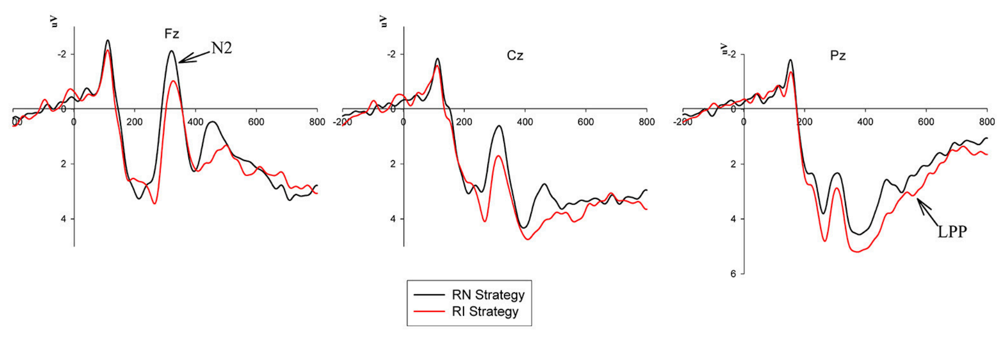

FIGURE 4 | Grand-average ERP waveforms of the frontal, central and parietal regions collected from the Fz, Cz, and Pz electrodes. Comparison of the amplitudes of the N2 and LPP components between the two conditions: the RI strategy vs. the RN strategy.

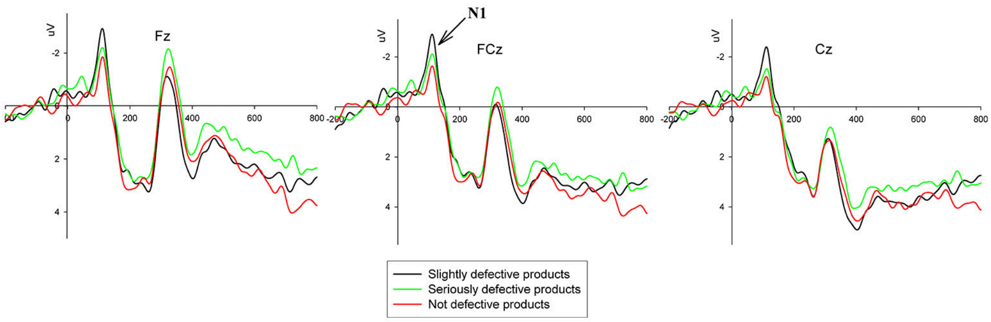

FIGURE 5 | Grand-average ERP waveforms of the frontal, fronto-central and central regions recorded from the Fz, FCz, and Cz electrodes. N1 amplitude comparison of the three product conditions, i.e., slightly defective products vs. seriously defective products vs. not defective products.

task difficulty, the slightly defective product condition required more mental resources to complete the rating task, which led to longer RTs. However, there was no significant difference between the RI strategy and the RN strategy, and there was no interaction effect between the product quality and the coupon strategy.

At the brain level, three components (N1, N2, and LPP) were identified in this study. N1, as an early ERP component, can reflect early automatic perceptual processes; this component has been found to be affected by attentional factors (e.g., Luck et al., 1994) and perceptual difficulty (Handy and Mangun, 2000). We found a significant main effect of product quality on the amplitude of the N1 component. The slightly defective products elicited higher N1 amplitudes than the seriously defective products and the not defective products, with no difference in N1 amplitude between the latter two. These results indicated that the participants perceived the perceptual difficulty associated with the slightly defective products at an early stage and paid more attention to processing them. Combined with the results of the RTs, we speculated that the decision of whether to give a five-star rating for the slightly defective products was more difficult than the other decisions. The difficulty of this decision could be automatically perceived during an early stage at the brain level and led to longer RTs at the behavioral level. However, the different coupon strategies did not evoke differences in the N1 amplitude, indicating that the coupon strategy factor was not deeply processed at an early stage.

The N2 component, as aforementioned in the introduction section, could reflect the process of detecting conflicting information (Van Veen and Carter, 2002; Ma et al., 2007, 2010; Folstein and Van Petten, 2008; Lahat et al., 2013), for which stronger cognitive conflicts induce larger N2 amplitudes (Fu et al., 2017). Monetary incentives make participants less sensitive to conflict or distress by communal values, which increases the likelihood of self-interested or immoral behavior (Cullen et al., 1985; Agnew, 1994; Vohs et al., 2006, 2008; Kouchaki et al., 2013). Thus, different forms of monetary access could reduce the conflicted perception of immoral behaviors to different degrees, which can be reflected by the amplitude deflection of the N2 component. In the current study, the RI strategy elicited a less negative N2 component than the RN strategy, which indicated that the participants detected less conflict in giving a five-star rating in response to the RI strategy than in response to the RN strategy. More specifically, the goal-related monetary rewards obtained from the RI strategy decreased the cognitive conflict compared to the goal-unrelated monetary rewards obtained from the RN strategy, as the former strategy made participants more willing to give five-star ratings to gain the reward.

Moreover, an obvious LPP component was observed from 400-600 ms. The LPP component has been reported to be associated with the conflict-resolution processing of stimuli evaluation (Chiu Loke et al., 2011; Yoder and Decety, 2014; Wang et al., 2016) and to be sensitive to the motivational significance of stimuli (Nieuwenhuis et al., 2003; San Martín, 2012). In the current study, after detecting the conflict, as reflected by the N2 component, a controlled and elaborate process was deployed for conflict resolution, which was reflected by the LPP component. The LPP amplitude that was evoked by the RI strategy was larger than that evoked by the RN strategy, which showed that the RI strategy had a greater incentive effect for the subjects to resolve the conflict than the RN strategy. Though the same amount of cash coupons were returned to the consumers, setting a related goal evoked a stronger motivation than not doing so. This incentive effect still existed even if the action required to achieve the goal was immoral.

The N1, N2, and LPP ERP components in the current study, may reflect the three-stage process involving how coupon strategy and quality information affect the fake rating behavior of consumers in e-commerce. The first stage was automatic sensory processing, which was reflected by the N1 component. The subjects automatically perceived the difficulty of the different levels, which was affected by the product quality information with no significant processing of the coupon strategy; the second stage involved the processing required for conflict detection, which was reflected by the N2 component. According to the different coupon strategies, the subjects detected different levels of cognitive conflict in the task of giving five-star ratings to the products with different qualities. The third stage involved motivational and conflict-resolution processing, as reflected by the LPP component, and the different coupon strategies were controllably analyzed and evaluated.

The three-stage process related to the fake rating behaviors resulting from different marketing strategies exhibited some similarities to the neural processes involved in moral decision-making, which include automatic processes (N1), emotional perception processes (N2) and controlled and elaborative processes (LPP) (Yoder and Decety, 2014; Gui et al., 2016). As mentioned in the introduction section, money can increase the likelihood of self-focused or immoral behavior (Cullen et al., 1985; Agnew, 1994; Vohs et al., 2006; Vohs and Schooler, 2008; Kouchaki et al., 2013). The cash coupons in the current study were specific monetary rewards, meaning that they could also lead to relatively self-interested rating behaviors. The fake five-star rating behaviors induced by the cash coupons have great impacts on other consumers' attitudes and purchase decisions. Thus, giving a fake rating could be considered an immoral behavior to some extent.

With the growing popularity of online shopping, fake online review has drawn increasing scholarly attention. The present study was undertaken from the perspective of consumers and used ERP measures to investigate if monetary reward offered by online sellers could give rise to consumers' fake rating behavior and how. We conjecture that the ERP findings of the current study might to a certain extent reflect the general tendencies of the neurocognitive processes underlying fake rating behavior. A fake rating is a rating not in line with the truth. Thus, giving a fake rating is similar to deception, which in many cases is a type of immoral behavior and may result in greater cognitive conflict than giving a truthful rating, which could be reflected by the N2 component (Wu et al., 2009; Suchotzki et al., 2015; Fu et al., 2017). Moreover, a related goal for the consumers, such as earning a certain amount of monetary reward and maintaining good interpersonal relationship, could not only alleviate the perceptual conflict but also prompt them to have greater incentives to give fake high-score ratings, which would be indicated by a smaller N2 and a larger LPP amplitude. Consequently, the illegal strategies used for manipulating fake rating behavior, particularly those capable of reducing cognitive conflict and strengthening incentives, should be strictly prohibited.

CONCLUSIONS

In this study, we used ERPs to explore which marketing strategy (RI vs. RN strategy) more strongly affects the online fake rating behavior of consumers. The RI strategy increased the rate of the five-star rating behavior compared with the RN strategy, with no observed moderating effect of the product quality. At the level of the brain, the N1, N2 and LPP components were found to reflect the neurophysiological processes involved in the task. The processing of the slightly defective products was perceived to be more difficult than the processing of the seriously defective and not defective products, as reflected by the N1 component. In addition, less conflict and stronger incentives were detected during the RI strategy than the RN strategy, as reflected by the N2 and LPP components, respectively. Generally, the goal-related monetary rewards involved in the RI strategy enhanced the falsity of the online comments by both reducing the perception of conflict and increasing the motivation, and these influences warrant additional future studies of fake online comments. To the best of our knowledge, the current study is among the first to explore the effects of money on fake rating behavior and the associated neural correlates. These findings could facilitate the study of online false reviewing and help platforms or government regulators uncover the possible harms from illegal online strategy manipulation.

AUTHOR CONTRIBUTIONS

CW, HF, and QM conceived and designed the experiments. CW, YL, and QM performed the experiments. CW, YL, and XL analyzed the data. CW, XL, and HF wrote and refined the article. CW, WF, and HF participated in the revision of the article.

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Corrigendum: The Effects of Money on Fake Rating Behavior in E-Commerce: Electrophysiological Time Course Evidence From Consumers

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The Temptation of Zero Price: Event-Related Potentials Evidence of How Price Framing Influences the Purchase of Bundles

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Studies have revealed that consumers are susceptible to price framing effect, a common cognitive bias, due to their limited capacity in processing information. The effect of price framing in a bundling context and its neural correlates, however, remain not clearly characterized. The present study applied the event-related potentials (ERPs) approach to investigate the role of price framing in information processing and purchase decision making in a bundling context. Three price frames were created with practically identical total prices (with a maximum difference of ¥0.1, which was about equal to 0.016 US dollars) for a bundle with two components, a focal product and a tie-in product. In normal price condition (NP), both the focal and tie-in products were offered at a normal discounted price; in zero price condition (ZP), the tie-in product was offered free while the total price of the bundle remained the same as NP; whereas in low price condition (LP), the tie-in product was offered at a low token price (¥0.1), and the focal product shared the same price as the focal product of ZP. The behavioral results showed a higher purchase rate and a shorter reaction time for ZP in contrast to NP. Neurophysiologically, enlarged LPP amplitude was elicited by ZP relative to NP, suggesting that ZP triggered a stronger positive affect that could motivate decision to buy. Thus, this study provides both behavioral and neural evidence for how different price framing information is processed and ultimately gives rise to price framing effect in purchase decision making.

Keywords: price framing, bundle, affect, purchase decision, ERPs, LPP

INTRODUCTION

Nowadays, with the proliferation of electronic commerce (e-commerce), consumers are exposed to all varieties of products with large amounts of information prior to making purchase decisions. Though perfect information may lead to a better decision, the limitation of human beings' ability to process information has made purchase decision a difficult task for consumers (Cheng et al., 2014). Human cognitive bias, which is likely to inflict negative effect upon decision quality, has thereby attracted substantial attention (Cheng et al., 2014; Gamliel et al., 2016).

The attribute framing effect is one of the most noted decision biases, which refers to the phenomenon that people show inconsistency in preferences or choices when identical attribute information is provided in different ways (Tversky and Kahneman, 1981). In marketing studies, price is a type of attribute information of a product and plays an import role in consumer decision making. A number of studies have probed into the influence of price framing on consumers' perceptions and purchase intentions (Chen et al., 1998; Khan and Dhar, 2010; Schmitz and Ziebarth, 2017). Chen et al. (1998) framed a discount in percentage terms (% off) vs. dollar terms ($ off) on differentially priced products, and suggested that a discount framed in dollar terms was more effective in enhancing consumer purchase intention of high-price product, whereas the opposite was true for the low-price product. Hamilton and Srivastava (2008) examined the pricing effect when the total price of a product and/or service was partitioned into two or more mandatory components. They found that consumers' reactions to price framing were moderated by the perceived consumption benefit of the components. Price framing effect was also observed in the bundling context (Khan and Dhar, 2010; Goh and Bockstedt, 2013). Bundling is a marketing practice of selling two or more products as a single package for a special price. It was noted that the purchase likelihood was higher for cross-category bundle when the price reduction was described as savings on the relatively hedonic item instead of as savings on the utilitarian item (Khan and Dhar, 2010). Moreover, consumers' intention to buy a customized bundle of information goods as well as the size of chosen bundling was greatly impacted by different multipart pricing schemes (Goh and Bockstedt, 2013).

Bundling has turned out to be a popular practice for both online and offline marketers and bundle pricing decision has become a major concern (Sheikhzadeh and Elahi, 2013; Shaddy and Fishbach, 2017). However, so far, the influence of bundle price framing upon consumer decision making has not been fully understood. It has been suggested that when people have to make a choice between two products, they tend to switch their preference from the preferred more expensive product to the less preferred but cheaper alternative when the latter is offered at zero price (namely zero-price effect), since a free product could give rise to positive affective reactions (Shampanier et al., 2007; Votinov et al., 2016; Hüttel et al., in press). In the multi-component bundling context, however, it's not clearly known how consumers would perceive and react if one price frame contains a free component while the other doesn't, provided that the total prices in different price frames are identical.

In addition, prior researches have generally adopted behavioral approaches to explore the price framing effect. Given the significant role of internal processes in driving cognitive bias, it is critical to gain insight into the associated underlying neural mechanisms, particularly how the price framing on bundles affects information processing in our brain and subsequent purchase decision-making. The application of neuroscientific approaches to marketing (i.e., neuromarketing) is promising in elucidating consumers' underlying thoughts, feelings, and intentions (Gajewski et al., 2016; Schaefer et al., 2016; Goodman et al., 2017; Hsu, 2017). Gajewski et al. (2016), for instance, investigated the electrophysiological brain activity during simulated purchase decisions of technical products offered at different price levels and observed enhanced conflict processing for counter-conformity decisions (buy an expensive product or not to buy a cheap one) vs. conformity decisions (buy a cheap product or not to buy an expensive one), which was reflected by longer reaction times, an increased N2 and a reduced P3. Besides, a few researchers have recently attempted to uncover the neurocognitive processes of attribute framing effect. Take Jin et al. (2017) as an example, they presented participants with two attribute frames regarding the contents of woolen products (i.e., positive frame was described as fabric contents in the products and negative frame described as artificial fabric contents in the products), and demonstrated that compared with negative frames, positive frames attracted less attention at the early stage (smaller P2 amplitude), evoked less cognitive conflict (smaller P2-N2 complex) and led to higher evaluation (larger LPP amplitude).

Therefore, the primary aim of the current study was to uncover the neural underpinnings of the price framing effect in bundle purchase decision-making by electrophysiological techniques. To attain this goal, two major price frames were created with the same total price for a bundle with two products, including a relatively expensive focal product and a relatively cheap tie-in product. In one price frame, both the focal and tie-in product were offered at a normal price (normal price condition, NP). In the second price frame, the tie-in product was offered at zero price while the total price of the bundle remained the same (zero price condition, ZP). Furthermore, a recent study reported an interesting finding that for price promotions offering product upgrades, it could be more effective when the upgrade was offered at a small token price (e.g., buy a Canon camera and upgrade its memory capacity from 16G to 32G for ¥0.1) rather than for free (Mao, 2016). We speculate that the tie-in product in a bundle might be treated as an "upgrade" in Mao's study. To test if Mao's findings could extend to a general bundling context, a third experimental condition was created such that the tie-in product was offered at a low token price (¥0.1, which was about equal to 0.016 US dollars at the time of experiment), whereas the focal product was offered at the same price as the focal product of ZP (low price condition, LP). Altogether, this study included three experimental condition (i.e., NP, ZP, and LP) with practically identical total prices (with a maximum difference of ¥0.1). During the experiment, participants were asked to view each bundle and determine if they would buy it or not while their scalp electroencephalogram (EEG) were recorded. According to prior literature on purchase decision making (Zhao et al., 2015; Goto et al., 2017), the late positive potential (LPP) is of particular interest to the current study.

The LPP is a positivity belonging to the P300 family, generally arises at about 400 ms after stimulus onset and lasts for several 100 ms (Schupp et al., 2000). The latencies of LPP vary across studies but tend to be predominant between 400 and 800 ms (Codispoti et al., 2012). LPP has a widespread scalp distribution from the frontal to the parietal sites with maxima over central-parietal sites. LPP is sensitive to motivationally relevant stimuli, and thought to reflect overt, post-perceptive deliberative processing related to stimulus significance (Olofsson et al., 2008). Emotionally significant stimuli (e.g., pleasant and unpleasant stimuli) has been found to trigger augmented LPP relative to neutral stimuli, suggesting enhanced activation of motivational system in the brain, increased resource allocation and sustained attentive processing for motivationally relevant stimuli (Schupp et al., 2004; Ferrari et al., 2011; Leite et al., 2012). Neuromarketing studies have revealed similar findings. Pozharliev et al. (2015), for instance, asked the participants to passively view pictures of luxury and basic branded products and noted increased LPP amplitude for luxury goods in the social context. Moreover, Goto et al. (2017) designed a virtual shopping task which revealed a positive relationship between LPP amplitude and subjective preferences of products. Consequently, LPP could reflect preferences based on more elaborative and conscious cognitive processes (Goto et al., 2017).

In the current study, three different price frames were created. Previous studies have demonstrated that options with no downside (no cost) could elicit more positive affect, which serves as an input for consumer decision making (Shampanier et al., 2007; Baumbach, 2016; Votinov et al., 2016). Thus, we hypothesize that the positive affect induced by a free component in a bundle could facilitate purchase decisions such that ZP will lead to higher purchase rate and enhanced LPP amplitude compared to NP and LP.

METHODS

Participants

Thirty-three healthy right-handed undergraduates from Guangdong University of Technology participated in the study. All participants were native Chinese speakers with normal or corrected-to-normal visual acuity and without any history of neurological disorders or mental diseases. The experiment conformed to the Declaration of Helsinki and was approved by the Internal Review Board of the Laboratory of Neuromanagement and Decision Neuroscience, Guangdong University of Technology. Participants provided written informed consent prior to the experiment and were paid for their participation after the experiment. Data from four participants were excluded, three for excessive artifacts during EEG recording and one for noticing the experimental manipulation and the purpose of the study, resulting in 29 valid participants (15 females) ranging in age from 19 to 23 years (mean $\pm$ SD $= 20 \pm 2.1$).

Experimental Stimuli

We used color digital pictures of 90 products selected from JD.COM, one of the largest online retailers in China. A variety of products were included, such as food, drink, electronics, personal hygiene products, stationery and others, all of which were familiar to our participants. Forty-five bundles were created, each of which comprised two products, a relatively expensive focal product and a relatively cheap tie-in product. The two products in each bundle were functionally complementary or related (e.g., a power bank and a USB cable, a pack of coffee, and a mug). Three price frames were devised for each bundle. Therefore, there were 45 trials in each frame condition and 135 trials altogether. For NP, the original prices for each component of the bundle were calculated as the mean of the prices in two different online shops. In order to encourage the participants to buy bundles during the experiment, offered prices for each component in NP were discounted from the means of the prices by ∼20% (Knutson et al., 2007; Goto et al., 2017). For ZP, the tie-in product was offered at zero price while the total price of the bundle remains the same as NP. For LP, the tie-in product was offered at a low token price (¥0.1) while the focal product of LP had the same price as the focal product of ZP.

Experimental Procedure

Participants were comfortably seated on a chair in a dimly lit, sound attenuated room. The stimuli were presented centrally on a 19-inch computer monitor (1,280 $\times$ 1,024 pixels, 60 HZ) against a gray background at a distance of 90 cm in front of the participants. E-Prime 2.0 software (Psychology Software Tools Inc., Pittsburgh, PA, USA) was used to deliver the stimuli and a keypad was provided for participants to make responses. Prior to the formal experiment, participants received instructions about the task and were tested for task comprehension in the practice trials. Participants got a virtual allocation of ¥70, which could be used to buy the bundles during the experiment. As illustrated in **Figure 1**, each trial began with a central fixation cross for 1,000 ms, which was followed by the presentation of a bundle for 2,000 ms with a visual angle of $8^\circ \times 3.7^\circ$. The focal product was placed to the left of the cross and the tie-in product the other side. Next, an empty screen was displayed for 400–600 ms randomly. Afterwards, the bundle was again presented with the prices displayed in red below each component for 4,000 ms, during which participants had to decide whether to buy the bundle or not at the offered prices. The response-to-hand assignments were counterbalanced across individuals such that half of them were instructed to press "1" for "buy" and "3" for "not buy" while the opposite was true for the other half. The virtual allocation was reset for every trial. The 135 trials were pseudorandomly assigned to three blocks, and the order of trials was pseudorandom within each block such that different price frames on an identical bundle did not appear within three consecutive trials. The experiment lasted for about 22 min. After finishing all trials, participants were asked if they were clearly aware of the experimental manipulation and the researchers' true intent. If a participant was aware of these, then the data from this participant would be excluded from further analysis.

To ensure the participants' motivational engagement in the shopping task, one trial was randomly selected to be implemented after the experiment (Knutson et al., 2007; Goto et al., 2017). If the participant chose to buy the bundle in that trial, then the bundle was later shipped to the participant, and cash "savings" corresponding to the initial allocation (¥70) minus the total price of the chosen bundle was paid to the participant. If not, the participant received the full allocation (¥70) as payment. This approach was used to maximize the realism of the shopping task because participants had a real chance of getting one of the "purchased" bundles, and cash saving was an inherent part of price-based shopping behavior.

Moreover, in order to minimize possible biases produced by strategies built upon buying only a small subset of products, and following previous research (Goto et al., 2017), participants were informed before the experiment that they would lose money on their final cash savings if they failed to buy a sufficient number

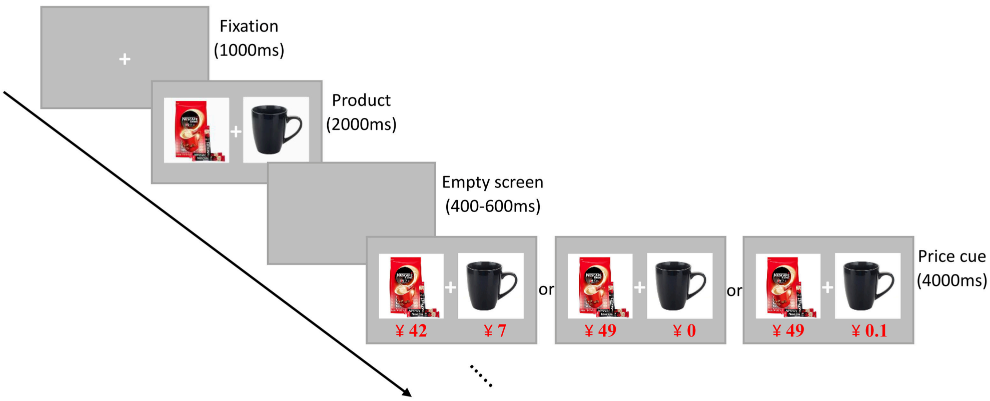

FIGURE 1 | Schematic illustration of one trial of the experimental task. Participants were instructed to make a "buy" or "not buy" decision after the presentation of the bundle along with price information.

of bundles. If the number of bundles bought was <20, then ¥20 would be subtracted from the savings. If the number was between 20 and 24, ¥10 would be lost. If this number was between 25 and 29, ¥5 would be lost. If more than 30 bundles were bought, no money would be lost at the end. As a matter of fact, all participants bought more than 30 bundles and not any penalty was applied.

EEG Data Recording and Analysis

The EEG was recorded with eego amplifier, using a Waveguard EEG Cap with 64 Ag/AgCl electrodes mounted according to the extended international 10–20 system (both manufactured by ANT Neuro, Enschede, Netherlands). Channel data were online band-pass-filtered from 0.1 to 100 Hz and recorded at a sampling rate of 500 HZ. The left mastoid served as on-line reference, and the EEG was off-line re-referenced to the mathematically averaged mastoids. Impedances were kept below 10 kΩ throughout the experiment.

EEG data were pre-processed off-line using ASALab 4.10.1 software (ANT Neuro, Enschede, Netherlands). Ocular artifacts were identified and corrected with the eye movement correction algorithm used in the ASALab program. The EEG was digitally filtered with a low-pass filter at 30 Hz (24 dB/Octave) and segmented into epochs of 1,000 ms, time-locked to price onset and included a 200 ms pre-stimulus baseline. Trials containing amplifier clipping, bursts of electromyography activity, or peak-to-peak deflection exceeding ±100 V were excluded from averaging. ERP averages were created separately for each experimental condition (i.e., NP, ZP, and LP).

As expected, a pronounced LPP component was elicited by different price frames. According to the visual observation of the grand average waveforms as well as previous studies on purchase decision making (Goto et al., 2017), three electrodes (Cz, CPz, and Pz) distributed among the centro-parietal sites were selected for LPP analysis. The average amplitude of LPP in the time window of 400–600 ms after the onset of price stimulus was submitted to a 3 (price frame: NP, ZP, and LP) × 3 (electrode: Cz, CPz, and Pz) repeated-measure ANOVA. The Greenhouse-Geisser correction (Greenhouse and Geisser, 1959) was applied in case of violation of the sphericity assumption (uncorrected dfs and corrected *p*-values were reported), and the Bonferroni correction was used for multiple paired comparisons.

RESULTS

Behavioral Data

Purchase Rate

Only trials that registered responses in <4 s after stimulus onset were included for behavioral analyses. The one-way repeated-measure ANOVA revealed a significant main effect of price frame on purchase rate, $F_{(2, 56)} = 7.793$, $p = 0.007$, $\eta_p^2 = 0.218$. As illustrated in **Figure 2A**, subsequent pairwise comparison indicated that participants made buy decisions more often in ZP (M = 0.550, S.E. = 0.033) compared to NP (M = 0.440, S.E. = 0.036, $p = 0.009$). But the contrast between ZP and LP (M = 0.529, S.E. = 0.032, $p = 0.241$), as well as the contrast between NP and LP ($p = 0.065$), was not significant.

Reaction Time

The ANOVA showed a significant main effect of price frame on reaction time (RT), $F_{(2, 56)} = 7.030$, $p = 0.004$, $\eta_p^2 = 0.201$. As illustrated in **Figure 2B**, pairwise comparison indicated shorter RT for ZP (M = 1,387.390 ms, S.E. = 86.931) than NP (M = 1,484.370 ms, S.E. = 95.516, $p = 0.004$). However, the contrast between ZP and LP (M = 1,406.854 ms, S.E. = 79.764, $p = 1.000$), as well as that between NP and LP ($p = 0.073$), was not significant.

ERP Data

As shown in **Figure 3**, the two-way repeated-measure ANOVA for LPP amplitude demonstrated a significant main effect of price frame, $F_{(2, 56)} = 4.220$, $p = 0.020$, $\eta_p^2 = 0.131$, and electrode, $F_{(2, 56)} = 56.792$, $p = 0.000$, $\eta_p^2 = 0.670$. The LPP amplitude elicited by ZP (M = 5.627 μV, S.E. = 0.696) was more positive than that by NP (M = 4.730 μV, S.E. = 0.725, $p = 0.013$). But

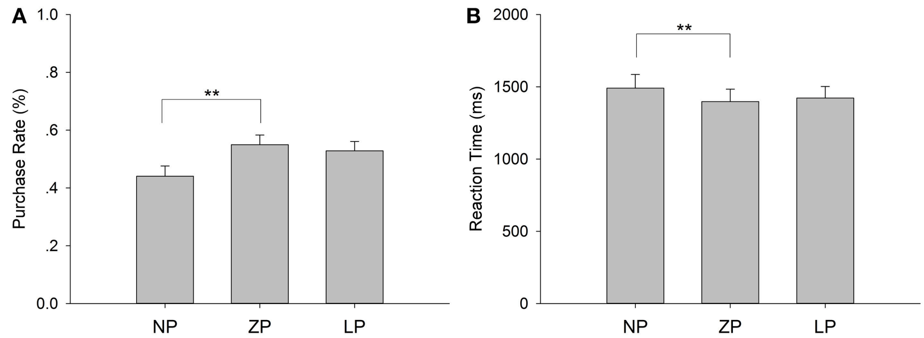

FIGURE 2 | Behavioral results. **(A)** The purchase rate for each condition and **(B)** the RT for each condition. The error bars indicate standard error of the mean. $^{**}p < 0.01$.

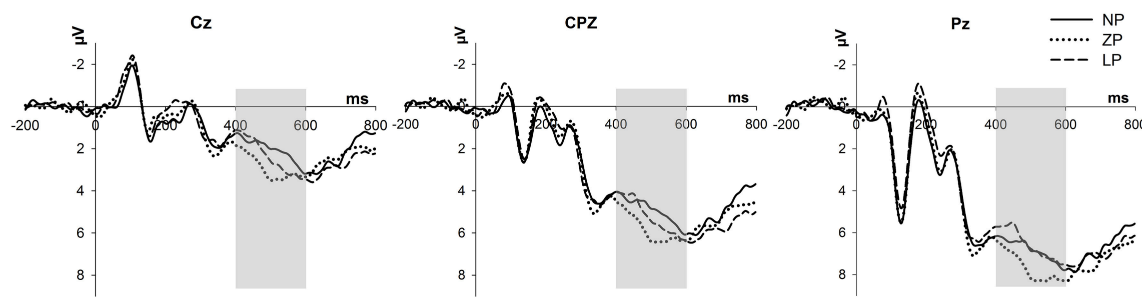

FIGURE 3 | ERP results. Grand-averaged ERP waveforms from three central electrodes (Cz, CPZ, and Pz) time-locked to the onset of price stimulus. The gray rectangles denote the time window for LPP analysis. Positive voltage is plotted downwards.

similar to the behavioral results, there was neither statistically significant difference of LPP amplitudes between ZP and LP (M = 4.979 μV, S.E. = 0.687, p = 0.279), nor between NP and LP (p = 1.000). Furthermore, the LPP amplitudes at Cz (M = 2.687 μV, S.E. = 0.652), CPz (M = 5.448 μV, S.E. = 0.724), and Pz (M = 7.202 μV, S.E. = 0.783) differed from each other ($ps < 0.05$). However, the interaction between price frame and electrode was not significant, $F_{(4, 112)} = 1.932$, $p = 0.110$, $\eta_p^2 = 0.065$.

Correlation Analyses Results

Two-tailed Pearson correlation analyses between the mean amplitude of LPP and RT were performed at the group level in order to explore if there were functional connections between one's brain activity and behavioral performance. It showed significant negative correlation between LPP amplitude and RT in NP ($r = -0.381$, p = 0.041), but no significant correlations between them in ZP ($r = -0.102$, $p = 0.600$), and LP ($r = -0.320$, $p = 0.091$).

DISCUSSION

The main goal of the present study was to elucidate how price framing influences purchase decision-making and its neural underpinnings. The behavioral results indicated that ZP led to a higher purchase rate and reduced RT than NP. Moreover, the ERP results showed larger LPP amplitude elicited by ZP in contrast to NP, providing neurophysiological evidence for the moderating effect of price framing on information processing and purchase decision making.

A remarkable price framing effect was discovered: people showed higher purchase rate when they were presented with bundles that contained a free component than when presented with bundles in which each component was offered at a normal price. Such a finding might be due to the positive affect induced by the zero-priced component (Shampanier et al., 2007; Nicolau, 2012; Nicolau and Sellers, 2012; Votinov et al., 2016). Previous studies have demonstrated that when people have to choose between two products, they tend to switch their preference from the preferred more expensive product to the less preferable but cheaper alternative when the cheaper option is offered for free (Shampanier et al., 2007; Votinov et al., 2016). A free offer could invoke a stronger positive affect and become extraordinary attractive since the zero price not only symbolizes no-cost but also implies extra benefit. This positive affect is used by consumers as a central input for decision making so that they're inclined toward the free option (Shampanier et al., 2007; Hüttel et al., in press). The zero price effect is not only confined to single products but also applies in multi-component contexts when one of the components becomes free (Nicolau and Sellers, 2012; Baumbach, 2016). In this study, stronger positive affect was evoked by the tie-in product when it was offered free rather than when offered at a normal price. This affect could extend to the evaluation of the bundle and made the bundle in ZP ostensibly more attractive. As a matter of fact, if consumers were rational persons, they would buy the same amount of bundles under different price frames since the total price of a bundle remained the same across different frames. We argue that people do not always act as rational economic models predict but instead they make decisions based substantially upon bounded rationality (Simon, 1956; Gigerenzer and Gaissmaier, 2011). For a purchase decision based on price information, affect may play a key role in the decision-making processes (Nicolau and Sellers, 2012; Somervuori and Ravaja, 2013), which give rise to the probability of non-rational economic behavior. When an individual's attention is focused on the positive aspect of a bundle (i.e., the zero-priced component), favorable associations could be evoked between the free component and its cost/benefit, leading to a higher purchase likelihood.

Moreover, people made purchase decisions faster in ZP rather than NP. It is proposed that RT is correlated with task difficulty and cognitive load (Wang et al., 2016). A shorter RT is generally suggestive of lower task difficulty and cognitive load (Cheng et al., 2014; Jin et al., 2017). In Jin et al. (2017)'s study, they asked participants to make purchase decisions in different attribute framing conditions (positive vs. negative), and found that the positive framing condition led to reduced RT relative to the negative framing condition, indicating that the stronger desirability of positive framing messages made purchase decisions easier. In the current study, the RT differentiation implicates that the task difficulty of ZP is lower than that of NP, and it entails less cognitive effort to make purchase decisions in ZP vs. NP. In line with Jin et al. (2017), ZP was more desirable to participants' expectation than NP, which might make purchase decision-making easier. A free component may lead people to feel more interested, elicit stronger positive affect, and accordingly capture a lot of attention. However, such an interpretation should be taken with caution since the lower difficulty of calculating a total price in ZP vs. NP could also contribute significantly to the shorter RT for ZP.

With regard to the ERPs component, we observed an effect of price framing on LPP in the 400–600 ms time window, with a topographical distribution across centro-parietal sites. LPP may be indicative of overt, post-perceptive deliberative cognitive processing related to stimulus significance (Olofsson et al., 2008). In consonance with the behavioral results, the neurophysiological results of this study showed larger LPP amplitude for ZP compared to NP, suggesting enhanced motivational engagement toward bundles with a free component, which increased resource allocation and facilitated sustained attentive processing (Schupp et al., 2004). A large number of studies have demonstrated that motivationally significant stimuli such as emotional stimuli, in contrast to neutral stimuli, lead to enlarged LPP amplitude (Schupp et al., 2004; Ferrari et al., 2011; Leite et al., 2012). In recent years, researchers have gained increasing interest in exploring the neural underpinnings of consumer emotion, attitude, and purchase intention (Pozharliev et al., 2015; Zhao et al., 2015; Bosshard et al., 2016; Goto et al., 2017; Wang et al., 2017). As Goto et al. (2017) noted, evaluating motivationally relevant consumer goods is quite similar to processing emotional stimuli in that they are usually associated with motivated attention. Zhao et al. (2015) reported that services with a high emotional value triggered a greater LPP amplitude, indicating that these services may motivate more positive emotions during purchase decision making. Pozharliev et al. (2015) examined the neural processes underlying passive viewing of luxury vs. basic branded goods, and showed increased LPP for luxury goods than for basic branded goods when the participants were together with another person, reflecting enhanced activation of motivational system in the brain for stimuli with higher emotional value. Furthermore, Goto et al. (2017) categorized ERP waveforms based on participants' preferences for a large variety of products and noted a positive relationship between LPP amplitude and subjective preferences, suggesting that subjective preferences were built on more elaborative and conscious cognitive processes. In a recent fMRI study, Votinov et al. (2016) engaged participants in a binary preference choice task with differentially priced products, which demonstrated a positive relationship between the activation of medial prefrontal cortex and the subjective happiness of obtaining free products and confirmed the role of affective evaluation in zero-price effect. As aforementioned in the current study, ZP might induce a stronger positive affect than NP because the former option contained a free component, which seemingly connoted no cost but extra value added to the bundle and made the offer highly attractive (Shampanier et al., 2007; Nicolau and Sellers, 2012; Votinov et al., 2016). Thereby, consistent with previous studies, the increased LPP amplitude for ZP vs. NP implies that ZP is motivationally more significant and is selected by the brain for heightened attentive processing, which to a large extent facilitates consumer purchase decision making, as evidenced by the higher purchase rate for ZP vs. NP.

It was worth noting that there were statistically significant differences at neither behavioral nor neural level between ZP and LP, as well as between NP and LP. The contrast between ZP and LP was of particular interest to this study. As Mao (2016) noted, in the context of price promotions offering product upgrades, it generated greater sales when the upgrades were offered at a low token price (e.g., buy a Canon camera and upgrade its memory capacity from 16G to 32G for ¥0.1) rather than for free (e.g., buy a Canon camera and upgrade its memory capacity from 16G to 32G for free). He suggested that when an upgrade was offered at a low price, its perceived attractiveness would be enhanced due to that the consumers tended to compare the token price with the upgrade's normative value and found the token price disproportionally small relative to the retail price; whereas when an upgrade was offered free, consumers were prone to evaluate it with the amount of required purchase. However, a token-priced upgrade would be no more favorable when consumers were asked to consider deal savings before evaluating the deal, which suppressed relative thinking (Mao, 2016). Thereby, we surmise that two reasons may account for the undifferentiated responses toward ZP and LP. Firstly, participants were exposed to different price frames in the current study, rendering it rather difficult to change their mindset rapidly, which implied that participants were inclined to resort to a sole criteria (e.g., perceived absolute savings) for decision making. Additionally, a number of products were used as stimuli in this study, which made it impossible for participants to estimate the normative value of the tie-in products (thought they were familiar with the products per se) and compare it with the token price within a limited time.

Based upon the above findings and discussion, this study also has practical implications for marketers and retailers. Bundling is a constant strategy in retailing in pursuit of not only more sales per order but also developing customer loyalty. The advance in e-commerce (including mobile e-commerce) has boosted the application of bundling strategy. Understanding the impact of the price of each component on consumer response to the bundle may prompt managers to make effective pricing decisions, especially in nowadays when e-commerce enables consumers to organize bundles by themselves. Given a fixed total price, setting a zero price for the tie-in product could evoke stronger positive affect than setting a normal discounted price for each component in the bundle, and lead the consumers more likely to make "buy" decisions. In other words, the free component in a bundle may act as a bait that draws attention from consumers and makes them more willing to give the bundle a try (Nicolau and Sellers, 2012).

However there are several limitations of our study which have to be acknowledged. First, we didn't measure positive/negative emotion directly via subjective ratings and the inference about the involvement of affective/emotional processes in price framing effect relied largely on observed electrophysiological activities during the task. This kind of reasoning is called reverse inference. Though reverse inference is extremely prevalent in cognitive neuroscience and neuromarketing, its validity has been regarded by some researchers as limited (e.g., Lee et al., 2017). Yet some researchers asserted that reverse inference was not intrinsically weak when applied with caution (e.g., Hutzler, 2014). Future studies are needed to replicate our findings by taking subjective measures of emotion into account, which allow a direct comparison between behavioral and neural results and draw conclusions in a more comprehensive way. Second, the difficulty of calculating the total price was not strictly controlled across different experimental conditions. It might be relatively easier to calculate the total price in ZP vs. NP, since the former condition contained a zero-priced component. Thus it could be argued that the differences in RT, LPP amplitude and purchase rate between ZP and NP might be partly due to the differentiated cognitive demand induced by calculating the total price. It was difficult to rule out the influence of task difficulty in the current research paradigm. However, we conjecture that the higher purchase rate in ZP vs. NP could not be simply attributed to the lower task difficulty since task difficulty has been found to be associated more often with cognitive and behavioral efficiency (as reflected in RT and accuracy) but less often with purchase decision outcome. In addition, contrary to the present study, higher task difficulty and cognitive load could also be accompanied by higher purchase rate (Wang et al., 2016).

CONCLUSIONS

To summarize, the current study investigated the price framing effect and its associated underlying neural mechanisms in a bundling context, and demonstrated that different price frames were processed differently. The behavioral results showed that ZP, in contrast to NP, led to a higher purchase rate, suggesting a more positive affect elicited by the zero-priced component that motivated buying decision. Moreover, a shorter RT was observed for ZP instead of NP due to the lower processing difficulty. At the neural level, ZP triggered larger LPP amplitude than NP, which might be a result of the more positive affect induced by the former condition. Overall, this study took a preliminary step toward uncovering the neural correlates of price framing effect, which may benefit future marketing studies.

AUTHOR CONTRIBUTIONS

HM and HF conceived and designed the study. HM collected and analyzed the data. HF, HM, and HZ interpreted the data and drafted the manuscript. HM, ZM, HZ, CW, and HF reviewed and edited the manuscript. HF administered the project.

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Good News or Bad News, Which Do You Want First? The Importance of the Sequence and Organization of Information for Financial Decision-Making: A Neuro-Electrical Imaging Study

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Investment decisions are largely based on the information investors received from the target firm. Thaler introduced the hedonic editing framework, in which suggests that integration/segregation of information influence individual's perceived value. Meanwhile, when evaluating the evidence and information in a sequence, order effect and biases have been found to have an impact in various areas. In this research, the influence of the Organization of Information (Integration vs. Segregation) and the Sequence of Information (Negative-Positive order vs. Positive-Negative order) on individual's investment decision-making both at the behavioral level (decision) and neurometrix level (measured by an individual's emotion and Approach Withdraw tendency) was assessed for the three groups of information: a piece of Big Positive Information and a piece of Small Negative Information, a piece of Big Negative Information and a piece of Small Positive Information, and a piece of Small Negative information. The behavioral results, which are an individual's final investment decision, were consistent for all three scenarios. In general, individuals will invest more/retire less when receiving two pieces of information in a Negative-Positive order. However, the neurometric results (Emotional Index, Approach Withdraw Index and results from LORETA) show differences among information groups. An effect of the Sequence of Information and the Organization of Information was found for the different scenarios. The results suggest that in the scenarios that involve large-scale information, the organization of information (Integration vs. Segregation) influences the emotion and Approach Withdraw tendency. The results of this investigation should provide insight for effective communication of information, especially when large-scale information is involved.

Keywords: hedonic editing hypothesis, order effects, financial decision-making, EEG, approach/avoidance, emotion, LORETA

INTRODUCTION

Investment decisions are largely based on the information investors receive from target firms (Clor-Proell, 2009). These pieces of information predict actual and potential gains and losses. For individual gains and losses, Thaler (1985, 2018) introduced the notion of hedonic editing. The framework of hedonic editing was derived from Kahneman and Tversky (1979) prospect theory, based on the assumption that in performing mental accounting, individuals tend to frame multiple forms of information in a manner that results in the highest perceived value. The hedonic framing hypothesis suggests that, in some situations the highest perceived value may be achieved by integration of information, whereas in others situations the segregation of multiple forms of information can maximize perceived value. More specifically, the form of the information is better accepted if; (1) a decrease in gain was presented in an integrated manner, (2) a small reduction in loss was presented in a segregated manner. As such, individuals were happier if the information provided higher individual value (*vs.* the same information presented in the opposite manner).

Previous research has tested the hedonic framing hypothesis with results mainly consistent with theory (Thaler, 1985; Thaler and Johnson, 1990; Linville and Fischer, 1991; Cowley, 2008; Evers et al., 2016; Antonides and Ranyard, 2017). However, in the investment field, findings are mixed. For example, using sales records from 1991 to 1996 (i.e., non-experimental data), Lim (2006) evaluated investor preference for integrating or segregating outcomes to examine how capital gains and losses affect U.S. investors who sell multiple stocks on the same day. Result confirmed the hedonic framing hypothesis, namely, on the same day investors are more likely to bundle the sale of stocks trading below their purchase price ("losers") with the sale of stocks trading above their purchase price ("winners"). In contrast, results from another study by Lehenkari (2009), using showed how real stock market data from the Finland Stock Market, did not support the main hypothesis. In that study only weak evidence for the hedonic framing hypothesis was found: investors in the sample did not consistently integrate losses and segregate gains, nor was there any significant preference for realized mixed gains rather than losses. These data indicate that the application of hedonic editing and prospect theory to the financial settings and investment field is not straightforward.

A second crucial factor in a mixed information condition, with both positive and negative information flows, is the order of the information. When evaluating the evidence and information in sequence, order and bias have been found to have an impact in various areas of accounting, auditing, and financial reporting (e.g., Ashton and Ashton, 1988, 1990; Pinsker, 2007, 2011; Daigle et al., 2015). Hogarth and Einhorn (1992) demonstrated a Belief-adjustment model and defined the order effect as follows: "There are two pieces of evidence, A and B. Some subjects express an opinion after seeing the information in the order A-B. Others receive the information in the order B-A. An order effect occurs when opinions after A-B differ from those after B-A" (see review by Kahle et al., 2005). In contrast, the Bayes' normative model, a Belief-adjustment model, suggests that more weight is placed on the most recent piece of evidence, with final judgements depending on the sequence of the provided evidence. This is especially true in situations characterized by an equal number of mixed information types (i.e., containing both positive and negative information). Psychological and behavioral studies have demonstrated that information order can affect individual decisions. More precisely, when requested to evaluate a short series with mixed information, the decision-maker will place more weight on the latest information. Thus, differential weighting of the information will result in a "recency effect" (Ashton and Ashton, 1988, 1990; Tuttle et al., 1997; Pinsker, 2007, 2011).

For investment decision-making, most investigations have used a stock price judgement task to assess the impact of a simple informational series. The series of information is processed either by sequential processing (i.e., SbS, Step by Step), where the evaluation will be done after receiving the information, or by simultaneous processing (i.e., EoS, End of Sequence), where the evaluation will be completed after receiving all of the information [Ashton and Ashton (1988, 1990), Pinsker (2004), see review by Kahle et al., 2005]. During the task, upon the subsequent release of each disclosure (if sequential) or set of disclosures (if simultaneous), subjects are asked to re-value the company's stock price (based on their prior valuation) and rate the direction of each disclosure on a scale from −10 (very bad news) to +10 (very good news). This approach confirmed the predictions of the Belief-adjustment. For example, Tuttle et al. (1997) examined the sequence effect on the efficiency of the market and concluded that individual investors experienced the recency effect when they received four clues or combined pieces of information. Pinsker (2004) examined stock price valuations from unsophisticated investors given different conditions of information. Continuous conditions (SbS) were significant in the direction of the information provided. While periodic (EoS) conditions were not significant at the midpoint of information evaluation, before all information had been provided. However, recency was detected after information items were released. Further evaluations were made for long series of clues and information. Pinsker (2011) conducted analysis of 40 information clues presented either simultaneously or sequentially: the results suggest a recency effect for all conditions, with significantly greater recency effect for the sequential conditions relative to the simultaneous conditions.

Two variables: Organization of Information (either Segregated or Integrated) and Sequence of Information (either negative-positive or positive-negative) have been shown to influence an individual's judgement and decision-making. However, these variables have not been assessed simultaneously. Nor have possible interaction and moderation effects been assessed for both the Organization of Information and the Sequence of Information during individual decision-making. Furthermore, the neural correlates of decision-making during these circumstances have not been investigated. More recently, according to Damasio's theories (Damasio, 1994, 1999), "emotions" have taken a principal role in the decision-making process and are a guide to the final executed choice. Supporting Damasio's studies, Bargh and Chartrand (1999) affirmed that, although humans are definitely capable of conscious deliberation, many economically relevant decisions rely on automatic, fast, and effective processes which are not under direct volitional control.

Herein, cerebral activity by electroencephalographic (EEG) recording, the galvanic skin response (GSR), and heart rate (HR) were evaluated during decision-making. In particular, Approach Withdraw (Davidson, 2004) and emotional (Mauss and Robinson, 2009; Vecchiato et al., 2014a) indices were used to estimate the "internal" state of the investigated subjects.

Objectives

1) Test if the organization and order of information affect an individual's decision-making upon exposure to two pieces of information, simultaneously/separately and in a different order.
2) Evaluate the neuro-electrical correlates of decision-making during different experimental conditions. In particular, the neurometric correlates of the Organization of Information (two levels, either Segregated or Integrated) and Sequence of Information (two levels, either Negative-Positive or Positive-Negative) will be evaluated.

In this investigation, the behavioral level (individual's decision) and neurometric indices, via Emotional Index and Approach Withdraw Index (AWI), were used as dependent variables to measure the individual's decision when dealing with two pieces of mixed information (one piece of positive information and one piece of negative information) framed by different sequence and organization.

Hypotheses

Three groups of mixed information, which are corresponding to hedonic editing hypothesis, were evaluated.

A. One piece of Small Positive Information and one piece of Small Negative Information. (SP/SN)

Hypothesis 1a: the Individual is willing to invest more/retire less money when receiving these two pieces of information integrated than when receiving the information in the Negative-Positive order.
Hypothesis 1b: the Individual has a more positive/less negative emotion when receiving these two pieces of information integrated than when receiving the information in the Negative-Positive order.
Hypothesis 1c: the Individual has a higher approach/lower withdraw tendency when receiving these two pieces of information integrated than when receiving the information in the Negative-Positive order.

B. One piece of Big Positive Information and one piece of Small Negative Information; (BP/SN)

Hypothesis 2a: the Individual is willing to invest more when receiving these two pieces of information integrated than when receiving the information in the Negative-Positive order.
Hypothesis 2b: the Individual has a stronger positive emotion when receiving these two pieces of information integrated than when receiving the information in the Negative-Positive order.
Hypothesis 2c: the Individual has higher approach tendency/lower withdraw tendency when receiving these two pieces of information integrated than when receiving the information in the Negative-Positive order.

C. One piece of Big Negative Information and one piece of Small Positive Information; (BN/SP)

Hypothesis 3a: the Individual is willing to retire less money when receiving these two pieces of information segregated than when receiving the information in the Negative-Positive order.
Hypothesis 3b: the Individual has a less negative emotion when receiving these two pieces of information segregated than when receiving the information in the Negative-Positive order.
Hypothesis 3c: the Individual has a lower withdraw potential when receiving these two pieces of information segregated than when receiving the information in the Negative-Positive order.

The information group: one piece of big positive information and one piece of big negative information is not tested in this research. It is mainly because this information group does not mentioned in original work of hedonic editing. Meanwhile, we consider this scenario relevantly rear in the actual world, especially in integrated situation: two important and dramatic events with the opposite valence happen at the same time point.

MATERIALS AND METHODS

Participants

Subjects were 20 Masters students from Sapienza Università di Roma, 23–26 years of age of which nine were females and 11 male. By self-report, all subjects indicated at least a basic knowledge of economics and finance and an understanding of basic terms: i.e., at least "3" out of "5" (0 for "none," 3 for "basic," 5 for "professional" levels of understanding). One subject was excluded in that he could not distinguish the size of information, i.e., big from small. Another subject's results were not complete due to technical issues. Hence, 18 valid results were analyzed (1 female and 1 male subject were excluded). Fourteen HR/GSR results were analyzed in that four HR/GSR results were missing.

Informed consent was obtained from each subject after explanation of the study, which was approved by the local institutional ethics committee. The experiment was conducted following the principles outlined in the Declaration of Helsinki of 1975, as revised in 2000 and was approved by the Sapienza University of Rome Ethical Committee in Charge for the Department of Molecular Medicine. All the subjects received extra credits in their course for participating this study. They were told that the performance of the experiments determined how much extra points they could receive.

Stimulus Material and Procedure

Materials used were pieces of information that related to the state of a company. These materials were primarily derived from Tuttle et al. (1997), Pinsker (2007, 2011), and Daigle et al. (2015). All were properly translated into Italian. Each piece of information contained two to three sentences. Most information was presented in an auditing format including; operation loss/gain, negative cash flow/improving cash inflow from large customers, increasing/reducing costs, lost customer or market share/rapidly growing customer base, slow inventory turnover, product quality problem, expiration/gain of a patent on a key product, a likely infusion of equity capital, etc. The non-auditing format included layoff of employees, delay in releasing new products, and customer satisfaction.

Three groups of information were tested; a piece of Small Positive Information and a piece of Small Negative Information (SP/SN), a piece of Big Positive Information and a piece of Small Negative Information (BP/SN), and a piece of Big Negative information and a piece of Small Positive Information (BN/SP).

To determine how an individual's investment decision was affected by both Organization and Sequence of Information, a 2 × 2 within-subject design was used. The first examined variable was the Organization of Information, with a two-level manipulation. (1) Two pieces of Integrated information (0, two pieces of information). In these cases, the subject was first informed "no new information is released at the current moment by the company," and then the subject was presented simultaneously with two pieces of information. (2) Two pieces of Segregated information (one piece of information and then the other piece of information). In these cases, the subject was presented with one piece of information at two separate time periods. The second manipulated variable was the Sequence of Information: Two pieces of information presented either in a Negative-Positive order (N-P) or in a Positive-Negative order (P-N). **Table 1** summarizes all scenarios.

The adopted experimental task was similar to the Stock Price Judgement task used by Pinsker (2004, 2011). However, rather than asking the subjects to revalue the stock price, each subject was asked to make an investment decision, deciding how much of an investment would be made in the target company. With this behavioral task, a clearer indication of the individual's decision for each scenario was assessed.

At the beginning of each trial, subjects were informed that they had 1,000 Euro in cash and stock worth 1,000 Euro that have already been invested in Company A. Subjects were told that the Company will release a piece of information every 6 months. Subjects were then informed that two pieces of information related to the state of Company A would be provided. After reading the two pieces of information, the subjects had the opportunity to adjust their investment plan; (1) they could choose to invest more cash in Company A, (2) or they could choose to retire some or all of their money from the investment, (3) or they could make no change. The result of the decision, namely the total amount of money that was invested or retired was analyzed as the behavioral result (i.e., the main dependent variable measure).

TABLE 1 | Experiment design is listed for all three groups of information: SP/SN; BP/SN; BN/SP.

		Organization of the information	
		Integrated	**Segregated**
Sequence of information	Negative-Positive	(0, SN-SP) (0, SN-BP) (0, BN-SP)	(SN, SP) (SN, BP) (BN, SP)
	Positive-Negative	(0, SP-SN) (0, BP-SN) (0, SP-BN)	(SP, SN) (BP, SN) (SP, BN)

All scenarios are listed.

The experiments were conducted on computer with software Presentation (Neurobehaviral Systems Inc., Presentation Research License). The experiments were carefully programed in Presentation according to following procedure. In all scenarios (both Segregated and Integrated situations for all three groups of information), subjects were given the first piece of information, with a maximum 20″ for reading. After reading, subjects pressed the key for the next page where they rated the information from −10 (very negative) to 10 (very positive) based on how positive or negative the information was perceived. Then subjects were then given the second piece of information to read and to rate from −10 (very negative) to 10 (very positive) based on how negative or positive the information was perceived. On the next page, subjects were asked to consider their reasons to either invest or retire, for 30 s. Afterward, subjects had 10″ to type their decision: i.e., how much money to invest or retire. In addition, they had 5″ to justify their decision in order to ensure that the protocol was followed (these were not used as dependent variables).

The presentation of each trial was randomized for each group of information (SP/SN, BP/SN, BN/SP). That is, for each of the three groups, the four Organization and Sequence possibilities were randomized (e.g., in the first group (SP, SN), the four possibilities were: 0, SN-SP; SN, SP; 0, SP-SN; SP, SN). EEG and HR/GSR measurements (see details below) were recorded throughout the experimental procedure.

Manipulation Check

The aim of this investigation was to test an individual's investment decisions based on information provided by differing organization and sequence patterns resulting from a series of statements either; very negative, small negative, very positive, or small positive. Initially it was necessary to measure how the subjects perceived the negativity or positivity of each received statement. For this reason, all statements had been previously validated through a manipulation check carried out with the same group of subjects. This procedure was conducted during a separate appointment 3–5 days before the experiment.

Subjects were required to read and to evaluate the materials by use of an international online platform, used in psychological research, that delivers questions and records answers via the Internet (Unipark©, made available from Sapienza Università di Roma's subscription at the Dipartimento di Psicologia dei Processi di Sviluppo e Socializzazione). After reading one piece of information, subjects rated the information from −10 (very negative) to 10 (very positive) based on how positive or negative the information was perceived (see **Table 2** for details). Information rated between 8 and 10 was considered Big Positive Information; the information rated between 2 and

TABLE 2 | Categorization and selection of information based on participant's rating score for each piece of information.

Participant's rating range	Categorization of information
Between 8 and 10;	Big Positive Information;
Between 2 and 5;	Small Positive Information;
Between −10 and −8;	Big Negative Information;
Between −5 and −2;	Small Negative Information;

5 was considered Small Positive Information; the information rated between −10 and −8 was considered Big Negative Information; the information rated between −5 and −2 was considered Small Negative Information. Only these four types of information met the criteria for inclusion in the following experiment.

Neurometric Data Acquisition

EEG Data

Subject's cerebral activity was recorded by means of a portable EEG system (BEPlus and Galileo software, EBneuro, Italy). Informed consent was obtained from each subject after explanation of the study, which was approved by the local institutional ethics committee. All subjects were comfortably seated on a reclining chair, in an electrically-shielded, dimly-lit room. Sixty four electrodes were arranged according to the 10–20 international system. Initially, recordings were extra-cerebrally referred and then converted to an average reference off-line. EEG activity was collected at a sampling rate of 256 Hz with the impedances below 5 kΩ. Each EEG trace was then converted into a Brain Vision format (BrainAmp, Brainproducts GmbH, Germany) for signal pre-processing and artifact detection, filtering, and segmentation. The EEG signals were band pass filtered at 1–45 Hz and depurated of ocular artifacts by Independent Component Analysis (ICA). The EEG data were re-referenced by computing the Common Average Reference (CAR). For each subject, the Individual Alpha Frequency (IAF) was estimated in order to define the frequency bands of interest according to the methods suggested by the relevant scientific literature (Klimesch, 1999).

Cardiac and Galvanic Skin Response Data

The considered autonomic activities, namely Galvanic Skin Response (GSR) and Heart Rate (HR), were recorded with the Nexus-10 system (Mind Media, Netherlands) with a sampling rate of 32 Hz. Skin conductance was recorded by the constant voltage method (0.5 V). Ag–AgCl electrodes (8 mm in diameter for active area) were attached to the palmar side of the middle phalanges of the second and third fingers of the participant's non-dominant hand by means of a velcro fastener. The company also provided disposable Ag–AgCl electrodes to acquire the HR signal. Before applying the sensors to the subject's skin, the surface was cleaned following procedures and suggestions previously published (Boucsein, 2012). GSR and HR signals were continuously acquired for the entire duration of the experiment and then filtered and segmented with in-house MATLAB software. For the GSR signal, a Continuous Decomposition Analysis was performed. The HR signal was obtained using the Pan Tompkins algorithm for the gathered electrocardiographic signals (Pan and Tompkins, 1985). In an attempt to match GSR and HR signals, the circumplex model for affect plane was used, where the coordinates of a point in space were defined by the HR (horizontal axis) that describes the valence phenomena and by the GSR (vertical axis) that describes the arousal phenomena (Russell and Barrett, 1999).

Approach Withdraw Index (AWI)

Specific attention was given to the frontal scalp areas overlying the prefrontal cortices. Several studies (e.g., Davidson, 2004; Maglione et al., 2015; Cartocci et al., 2016a,b,c, 2017a,b,c,d; Cherubino et al., 2016a,b; Marsella et al., 2017; Modica et al., 2017) describe the frontal cortex as an area of interest for the analysis of this approach for withdrawal attitude (Davidson, 2004) and cerebral effort (Klimesch, 1999). In order to define AWI based on the EEG frontal asymmetry theory, imbalance was computed as the difference between the average EEG power of right and left recorded channels using the following formula.

$$AW = \frac{1}{N_P}\sum\nolimits_{i\in P} x^2_{\alpha_i}(t) - \frac{1}{N_Q}\sum\nolimits_{i\in Q} y^2_{\alpha_i}(t) = \\ = Average\ Power_{\alpha_{right,frontal}} - Average\ Power_{\alpha_{left,frontal}} . \quad (1)$$

x_{α_i} and y_{α_i} represent the EEG channels in the alpha band that were recorded from the right and left frontal lobes, respectively. In addition, P and Q were two sets of EEG sensors employed and described as follows:

$$P = \{Fp2,\ AF6,\ AF4,\ F4\} \text{ and } Q = \{Fp1,\ AF7,\ AF3,\ F5\}.$$

N_P and N_Q represent the cardinality of these two sets of channels. According to Davidson's theory (Davidson, 2004), an increase in AWI will be related to an increase in the approach of the subject during decision-making and vice versa.

For each individual, the AWI signal was estimated during the entire decision-making time interval. Then, the signal was standardized by using the mean and variance of the AWI signal estimated during the baseline intervals recorded at the beginning and at the end of the experiment. The AWI of the entire experimental group was obtained by averaging the different standardized individual AWI.

Positive AWI values indicated an approach motivation toward the stimulus expressed by the subject, while negative AWI values, a withdrawal tendency.

Emotional Index

The emotional index was defined as previous described (Vecchiato et al., 2014b) by accounting for the GSR and HR signals for each individual during the decision-making task. For variables, an affect circumplex plane (Russell and Barrett, 1999) was constructed where emotions were defined in terms of arousal and their emotional valence. As a proxy for arousal, the values of the estimated GSR measurements and HR were used as a proxy for emotional valence. Standardized values for *GSR and HR* were then assessed by using the same baselines employed in the definition of the AWI index, using *GSRz* and *HRz* values for the generation of an Emotional Index *(EI)*. The *EI* was defined as follows:

$$EI = 1 - \frac{\beta}{\pi}. \quad (2)$$

Where:

$$\beta = \begin{cases} \frac{3}{2}\pi + \pi - \vartheta \text{ if } GSR_Z \geq 0,\ HR_Z \leq 0 \\ \frac{\pi}{2} - \vartheta \text{ otherwise} \end{cases}. \quad (3)$$

GSR_Z *and* HR_Z represent the z-score variables for GSR and HR respectively; ϑ, in radians, is measured as *arctang* (HR_Z, GSR_Z). Therefore, the angle β was defined in order to transform the domain of ϑ from [-π, π] to [0, 2 π] to obtain the EI varying between [−1, 1]. In this manner, β was calculated two ways. According to Equations 2 and 3 and the affect circumplex (Russell and Barrett, 1999), negative ($HR_Z < 0$) and positive ($HR_Z > 0$) values of the *EI* are related to negative and positive emotions, respectively, spanning the whole affect circumplex.

Low Resolution Tomography (LORETA)

To evaluate the three-dimensional distribution of estimated cerebral activity, exact Low Resolution Tomography (eLORETA) software was used (Pascual-Marqui et al., 2011). eLORETA is a validated method for localizing the electric activity in the brain based on multichannel surface EEG recordings (Horacek et al., 2007; Pascual-Marqui et al., 2011, 2014; Müller et al., 2016). Such LORETA methodology was used to represent at the cortical level the results obtained for the whole EEG collected during the decision-making time period. No specific hypothesis was formulated for the estimated cortical activity by LORETA during decision-making by the subjects. However, results were used to describe significant effects. The cortical areas with spectral EEG power that differ significantly in particular frequency bands (Theta, Alpha) between two particular conditions are shown in color (from blue to red), while the cortical areas in which there was no statistical difference are shown in gray. Statistical analysis was performed taking into account the possibility for Type I errors, by using the Holm correction (Pascual-Marqui et al., 2011). The statistical tests were performed at a nominal significance of 5% (Holm corrected for multiple comparisons). A color code was used to depict statistical significance between A and B conditions: a red color is a significant increase in EEG power spectra, A vs. B, a blue color is not significant. It is worth noting that in the Alpha band, an increase in EEG power spectra was associated with a decrease in cortical activity in the frequency band, with the opposite true as well. In the Theta band, an increase in EEG power spectra was associated with an increase in cortical activity in the frequency band, with the opposite true as well (Pascual-Marqui et al., 2011).

Statistical Analysis and Qualitative Description

Statistical analyses were performed with SPSS 15.0 (SPSS Inc., 1989–2006, United States). Specifically, repeated-measures ANOVAs for factors (Organization of Information, Sequence of Information) were carried out for the behavioral measures (the total amount of investment) and for neurometric indices (i.e., AWI and EI). Greenhouse-Geisser corrections were applied if the assumption of sphericity was violated.

RESULTS

One Piece of Small Positive Information and One Piece of Small Negative Information [SP/SN]

Table 3 reports the general results for the SP/SN information scenario. When subjects were given one piece of Small Positive Information and one piece of Small Negative Information, the variable integration/segregation did not show any statistical significance in the three indices: i.e., Investment, Emotional Index, and AWI. The variable order of information shows statistical significance for Investment and AWI, but no significance for Emotional Index, which suggests no emotional involvement during such a decision.

Hypothesis 1a: **Figure 1** shows the amount of total investment according to the Order of Information [$F_{(1,17)} = 4.711$, $p = 0.044$]. This significant result indicates that the investment was higher when two pieces of information were received according to the order Negative-Positive (*vs.* Positive-Negative), suggesting a recency effect, which is consistent with the hypothesis.

Hypothesis 1b: For Emotional Index, there was no statistical significance due to either organization or the order of information.

Hypothesis 1c: **Figure 2** shows the Order of Information main effect [$F_{(1,17)} = 7.486$, $p = 0.014$] for the Approach Withdraw Index: Subjects had higher average values for approach potentials when a piece of positive information was presented second, which confirms a recency effect.

Cortical activity was estimated by the LORETA approach (**Figure 3**, only frontal areas were assessed). Results show that comparison of (0, SN+SP) to (0, SP+SN) was coherent with **Figure 2**. When the information was integrated, there was lower activation in the left prefontal area compared to the right in the scenario (0, SN+SP) than in the (0, SP+SN) scenario. This result indicates a stronger withdrawal tendency in the presentation of (0, SP+SN) and comfirms the recency effect with subjects more influenced by the most recent information when the information

TABLE 3 | Summary of statistical results for the information scenario SP/SN.

	Investment	Emotion	AWI
Integration/segregation	–	–	–
Negative-positive/positive-negative	X	–	X

"X" indicates statistical significance for the measure."-"indicates no statistical significance for the measure.

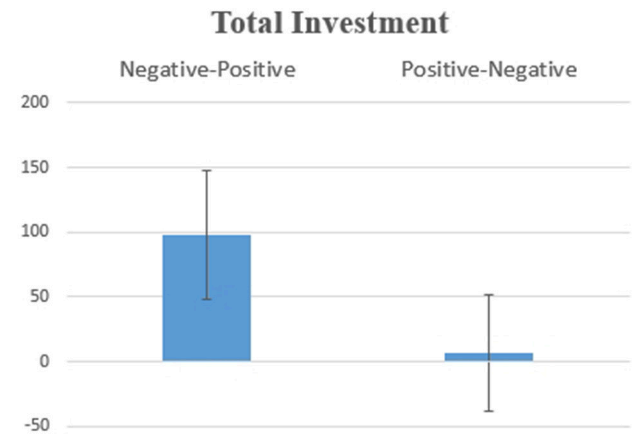

FIGURE 1 | Average values for the total investment decision for SP/SN. The difference was statistically significant at $F_{(1,17)} = 4.711$, $p = 0.044$.

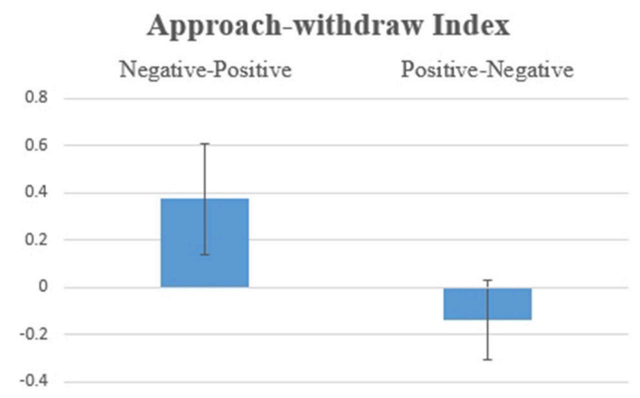

FIGURE 2 | Average values for the Approach Withdraw Index for SP/SN: two pieces of information were presented in Negative-Positive vs. Positive-Negative order: differences were statistically significant at $F_{(1,17)} = 7.486$, $p = 0.014$.

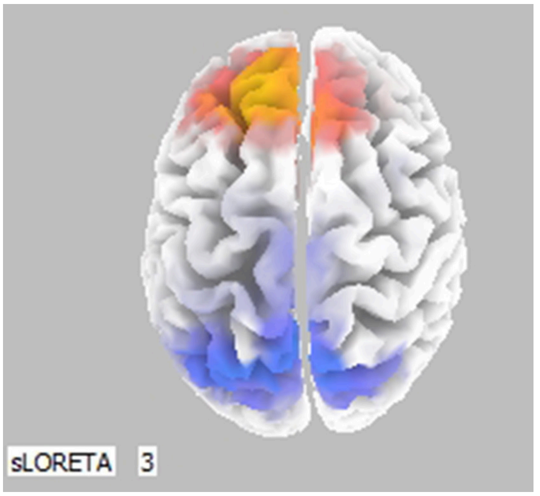

FIGURE 3 | Statistically significant cerebral activity was estimated by LORETA software in the Lower Alpha Band comparing two pieces of information presented in scenario (0, SN+SP) and scenario (0, SP+SN). Orange areas suggest a significant increase in cortical activity for the first scenario (O, SN+SP) with respect to the other (0, SP+SN). Blue colors suggest the opposite.

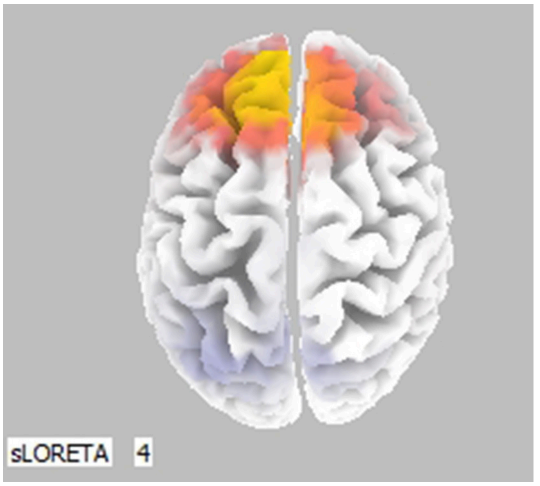

FIGURE 4 | Statistically significant cerebral activity was estimated by LORETA software in the Upper Alpha Band comparing two pieces of information presented for scenario (0, SN+SP) with scenario (SN, SP). Orange areas suggest a significant increase in cortical activity for the scenario (0, SN+SP) with respect to the other scenario.

was integrated. Specifically, when the second piece of information was positive, subjects had less withdrawal potential (orange colors in the frontal areas depicted in **Figure 3**).

For the LORETA results (**Figure 4**), when (0, SN+SP) and (SN, SP) were compared in the Upper Alpha Band, there was lower activation in the left prefrontal area compared to the right in (0, SN+SP) than in (SN, SP). With (SN, SP) subjects have a stronger withdrawal tendency. This result is consistent with Thaler's prediction that with information types like SN/SP, it is better to provide integrated rather than segregated information, as segregation will result in higher withdraw potential.

One Piece of Big Positive Information and One Piece of Small Negative Information [BP/SN]

Table 4 shows the general results for the information scenario BP/SN. When subjects were given one piece of Big Positive Information and one piece of Small Negative Information, the variable integration/segregation showed statistical significance in the biometric indices: Emotional Index and AWI, but no significance in the Behavioral Investment measure. The variable order of information showed statistical significance for the Investment measure but no significance for the biometric indices: Emotional Index and AWI.

Hypothesis 2a: **Figure 5** shows, for the amount of total investment, a marginally significant [$F_{(1,17)} = 3.615$, $p = 0.074$] effect for the Order of Information. This result indicates that

TABLE 4 | Summary of statistical results for the information scenario BP/SN.

	Investment	Emotion	AWI
Integration/segregation	–	X	X
Negative-positive/positive-negative	X	–	–

"X" indicates statistical significance for the measure."-"indicates no statistical significance for the measure.

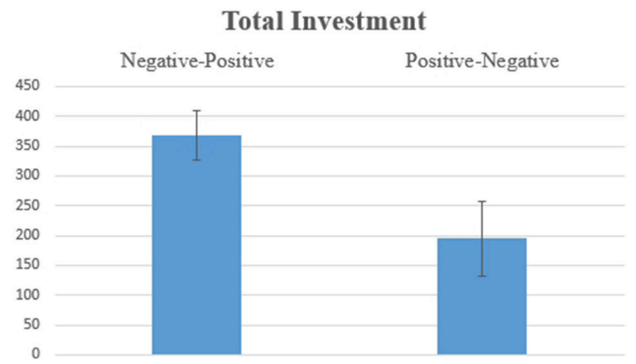

FIGURE 5 | Average values for the total investment decision for BP/SN. The difference was marginally significant at $F_{(1,17)} = 3.615$, $p = 0.074$.

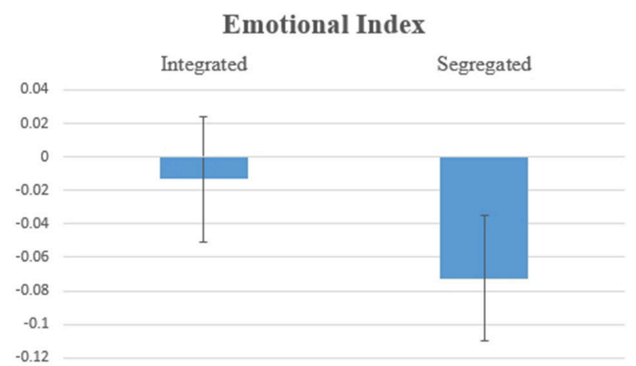

FIGURE 6 | Average values for Emotion Index for BP/SN, two pieces of information integrated vs. segregated. The difference was statistically significant at $F_{(1,13)} = 8.574$, $p = 0.012$.

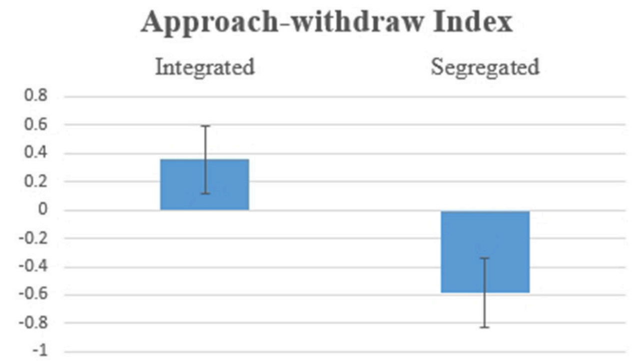

FIGURE 7 | Average values for the Approach Withdraw Index for BP/SN, two pieces of information integrated vs. segregated. The difference was statistically significant at $F_{(1,17)} = 11.373$, $p = 0.004$.

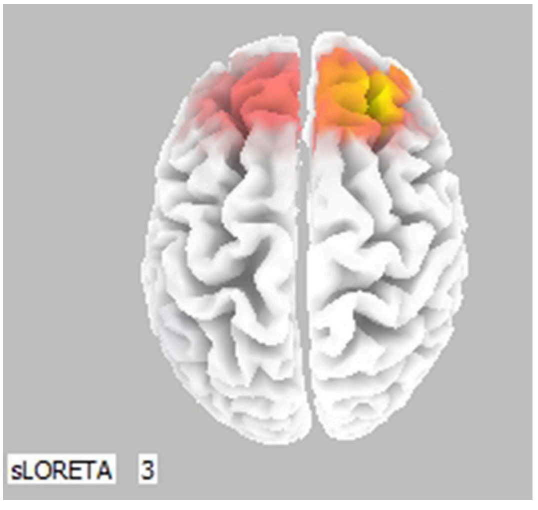

FIGURE 8 | Statistically significant cerebral activity was estimated by LORETA software for the Lower Alpha Band for comparison of two pieces of information in (SN, BP) and in (0, SN+BP). A similar result was generated in the Upper Alpha Band. Orange areas suggest a significant increase in cortical activity for the first scenario (SN, BP). For this experimental condition, there were no important difference in the cortical activities estimated by the two different frequency bands.

investment tends to be higher when the two pieces of information are in the order Negative-Positive, suggesting a tendency for a recency effect, which is partially consistent with the hypothesis.

Hypothesis 2b: **Figure 6** shows the results for Emotional Index, with a significant effect for the variable Organization of Information [$F_{(1,13)} = 8.574$, $p = 0.012$]. This result suggests higher Emotional Index when one piece of Big Positive Information and one piece of Small Negative Information are integrated.

Hypothesis 2c: The AWI was consistent with the Emotional Index, showing a significant effect [**Figure 7**; $F_{(1,17)} = 11.373$, $p = 0.004$] for the variable Organization of Information. In this information group, the average for the Integrated Information condition was higher than the average for the Segregated Information condition.

For the alpha band in the LORETA map (**Figure 8**), the lower activation in the right prefrontal area was observed by compariosn of (SN, BP) to (0, SN+BP). The result suggests a higher approach tendency when information was integrated in the Negative-Positive order.

Another significant LORETA map effect (see below, **Figure 9**) was found by comparison of (0, BP+SN) to (0, SN+BP). A lower activation in the right prefontal area was observed when comparing the scenario (0, BP+SN) to (0, SN+BP). Results indicated a recency effect when information was integrated. A stronger approach tenedncy was observed when information was presented Negative-Positive rather than Positive-Negative.

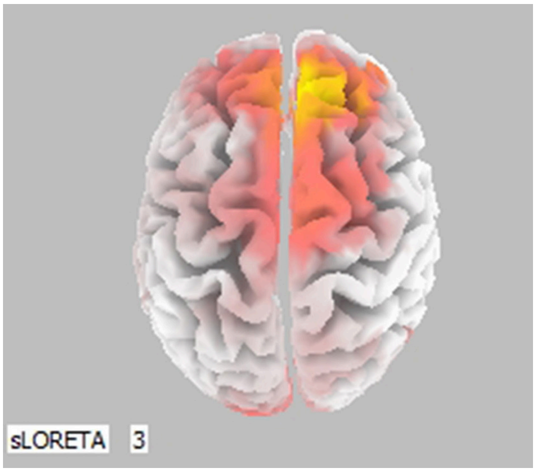

FIGURE 9 | Statistical significant cerebral activity was estimated by LORETA software in the Lower Alpha Band comparing two pieces of information presented in (0,BP+SN) with (0, SN+BP). A similar result was generated in the Upper Alpha Band. Orange areas suggests a significant increase in cortical activity for the first scenario (0, BP+SN).

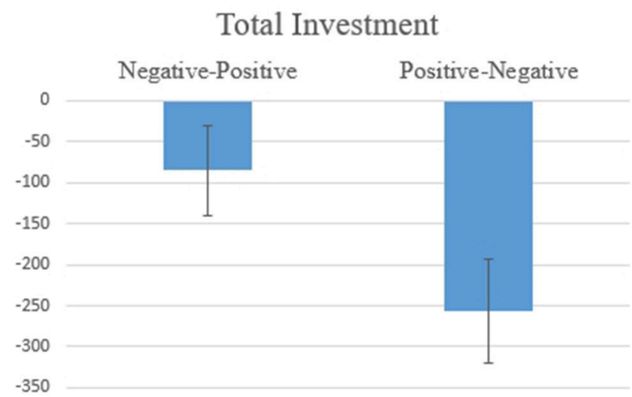

FIGURE 10 | Average values for the total Investment decision for BN/SP. The difference was statistically significant at $F_{(1,17)} = 4.590$, $p = 0.047$.

FIGURE 11 | Average values for the Emotional Index for BN/SP, two pieces of information Integrated vs. Segregated. The difference was statistically significant at $F_{(1,13)} = 4.871$, $p = 0.046$.

TABLE 5 | Summary of statistical results for BN/SP.

	Investment	Emotion	AWI
Integration/segregation	–	X	Interaction
Negative-positive/positive-negative	X	–	

"X" indicates a statistically significance effect for the variable."-"indicates that no statistical significance was shown for the variable.

One Piece of Big Negative Information and One Piece of Positive Information [BN/SP]

Table 5 shows results for BN/SP. When subjects were provided one piece of BN information and one piece of SP information, variable integration/segregation showed a statistically significant effect for the Biometric Indices, especially for the Emotional Index. No significant effect for the Investment Behavioral measure was observed. The variable Order of Information showed a statistically significant effect for the Investment measure but no significant effect for the Emotional Index. For the Approach Withdraw Index, there was an interaction between the two variables.

Hypothesis 3a: The amount of total investment showed a significant effect [$F_{(1,17)} = 4.590$, $p = 0.047$, **Figure 10**] for the Order of Information variable. The results indicate that investment was higher when two pieces of information were in the order Negative-Positive, suggesting a recency effect, which is partially consistent with the hypothesis.

Hypothesis 3b: Fort the Emotional Index, there was a significant effect for the variable Organization of Information [$F_{(1,13)} = 4.871$, $p = 0.046$, **Figure 11**], which is consistent with Thaler's principle: on average, individuals feel a less negative emotion when receiving two pieces of information Segregated instead of Integrated (herein a big negative and a small positive).

Hypothesis 3c: For the AWI, there was marginal significance for the interaction between Organization of Information and the Order of Information [$F_{(1,17)} = 3.720$, $p = 0.071$, **Figure 12**]. When the information was provided in the order Negative-Positive, the individual had a stronger willingness to approach when two pieces of information were presented separately rather than simultaneously [$F_{(1,17)} = 5.473$, $p = 0.032$]. Marginal significance [$F_{(1,17)} = 3.892$. $p = 0.065$] for the recency effect was observed when two pieces of information were segregated: Negative-Positive order was preferred when compared to Positive-Negative.

For the LORETA map (**Figure 13**), there was significant Alpha Band activation in the prefrontal area for comparisons of (SP, BN) with (0, SP+BN). (0, SP+BN) had a higher withdraw potential when compared to (SP, BN). The result suggests that with a Positive-Negative order, it is better separate the information rather than integrate it, which is consistent with Thaler's theory.

DISCUSSION

Humans are influenced by unrecognized and finely tuned affective mechanisms, which often play a decisive role in

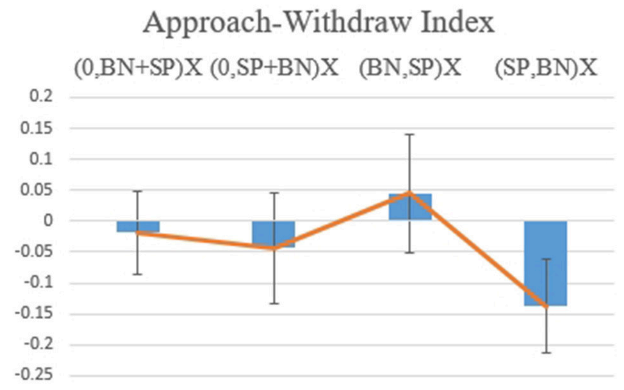

FIGURE 12 | Value for the Approach Withdraw Index for (0, BP+SN), (0, SN+BP), (BP, SN), and (SN, BP).

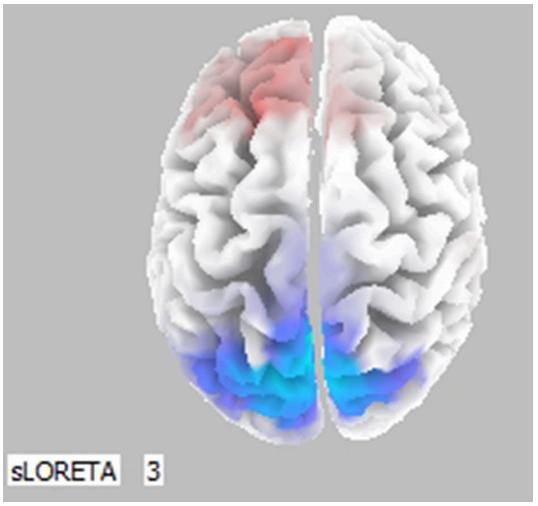

FIGURE 13 | Statistically significant cerebral activity was estimated by LORETA software in the Lower Alpha Band when two pieces of information were presented in (SP, BN) and in (0, SP+BN). Similar results were observed in the Upper Alpha Band. Orange areas suggest a significant increase in cortical activity for the first scenario (SP, BN) with respect to the other scenarios. Blue colors depict the opposite.

decision-making and action (Davidson and Irwin, 1999; Panksepp, 2004). Many of these processes were shaped by evolution to serve social purposes (Cacioppo and Berntson, 2002; Adolphs, 2008; Astolfi et al., 2011) while decision-making and evaluation in economic contexts are influenced by mechanisms dedicated to social interaction. In this study, we investigated the neuro-electric correlates of decision-making during differing experimental conditions related to the temporal presentation of economic information.

Based on Thaler's hedonic editing framework and the Belief-adjustment model, the influence of the Organization of Information (Integration vs. Segregation) and the Sequence of Information (Negative-Positive order vs. Positive-Negative order) on decision-making both at the behavioral level (decision) and neurometrix level (measured by an individual's emotion and Approach Withdraw tendency) was assessed for the three groups of information: SP/SN, BP/SN, BN/SP. The results of this study partially verified the hypotheses.

The behavioral results, which are an individual's final investment decision, were consistent for all three scenarios (SP/SN, BP. SN, BN/SP, see **Figures 1**, **5**, **10** in Results). In general, individuals will invest more/retire less when receiving two pieces of information in a Negative-Positive order. This result confirms previous findings (Ashton and Ashton, 1988, 1990; Tuttle et al., 1997), which suggest that for a short-series of mixed information, the subject's judgement exhibits the recency effect. For SP/SN, individuals invested 9.2% more when receiving two pieces of information in a Negative-Positive order than in a Positive-Negative order (average investment of 98.3 Euro vs. an average investment of 6.8 Euro). For BP/SN, individuals invested 36.8% more when receiving two pieces of information in a Negative-Positive order than in a Positive-Negative order (average investment of 367.9 Euro vs. average investment of 195.0 Euro). The amount of investment in a Negative-Positive order was 47.0% higher than in a Positive-Negative order. For BN/SP, individuals retired 17.2% less stock when receiving two pieces of information in a Negative-Positive order than in Positive-Negative order (average retirement of 84.8 Euro vs. average retirement of 257.1 Euro). The amount of retirement in Negative-Positive order was 67.0% lower than in a Negative-Positive order. From the behavioral results, the influence of information sequence was clear. The recency effect was found in all three groups. However, for the behavioral results, no significant difference was observed between the scenarios which two pieces of information were received Segregated or Integrated.

However, the neurometric results (Emotional Index, Approach Withdraw Index and results from LORETA) show differences among information groups. An effect of the Sequence of Information and the Organization of Information was found for the different scenarios.

For SP/SN, which represents an ordinary situation without large scale information, results show no statistical significance for Emotional Index. This result indicates less emotional involvement when information is small, suggesting a cognitive level of coping during such a scenario. Approach Withdraw Index, shows consistency with the behavioral results. The Order of Information, in particular the most recent information, affects an individual's decision: positive information immediately before the decision results in higher investment and a stronger approach potential. Whereas negative information immediately before the decision results in a stronger withdraw tendency and a lower investment/retirement of the money. This result is consistent with previous investigations that demonstrated the importance of information recency (Pinsker, 2004). The LORETA map comparing (0, SN+SP) to (0, SP+SN) confirms that when the second piece of information was negative, subjects had a stronger withdraw tendency. These results further stress the importance of the recency effect for not only behavioral decision making measures, confirming previous literature (Ashton and Ashton, 1988, 1990; Tuttle et al., 1997) but also for automatic cognitive processing measures, which is an innovative contribution of this investigation.

Moreover, these results suggest that for small pieces of negative and positive information, the order of information overrules the effect of the organization. Segregation or Integration of two small pieces of information does not affect an individual's investment decision as the hedonic editing theory predicts. With one exception for the LORETA map when comparing (0, SN+SP) to (SN, SP), the results indicate the best strategy Integration rather than Segregation in a Negative-Positive order, consistent with Thaler (1999) theory. Overall, the order of small scale information received determines priority in decision-making.

In the second and third hypotheses, the focus was on large-scale information. There are two asymmetrical cases; (1) one piece of Big Positive Information and one piece of Small Negative Information, (2) one piece of Big Negative Information and one piece of Small Positive Information. For these cases, Emotional Index influenced decision-making at the level of the individual's Approach Withdraw potential.

For BP/SN, the Emotional Index was significant as a variable of the Organization of Information confirming Thaler's theory concerning the integration/segregation of such pieces of information where positive emotion is higher in an Integrated vs. a Segregated condition. AWI results were consistent with Emotional Index results, indicating a higher approach potential for Integrated conditions. Thus, with a piece of Big Positive Information and a piece of Small Negative Information, it is best to integrate the two in order to boost both emotion and approach potentials. Support comes from the LORETA map, when (SN, BP) was compared to (0, SN+BP). When information was presented in the Negative-Positive order, Integration had a higher approach tendency. Nevertheless, even though AWI showed no significance for the effect of order, the LORETA map comparing (0, BP+SN) to (0, SN+BP) suggests the influence of order in this case. When information was integrated, Negative-Positive Order was favored over Positive-Negative. When big positive information was received after small negative information, subjects had a higher approach tendency, consistent with a recency effect.

For all four scenarios of BN/SP, emotion was negative, which may be due to stronger negative information rather than positive, with the perception that overall information was negative. Emotional Index was influenced by the Organization of Information with negative emotion higher when integrated. In other words, to diminish the emotional impact of Big Negative Information, it should be Segregated. AWI shows a similar trend, although significance depends on interaction between order and organization, indicating a preference for approach tendency. Segregation plus order are influenced by the recency effect, with Small Positive Information best when presented last. By LORETA map of the whole brain, a frontal alpha asymmetry was demonstrated with a Positive-Negative order. The results suggest that with a Positive-Negative order there is higher withdraw tendency when information is presented segregated than Integrated. This result is consistent with Thaler's prediction that a small reduction in loss should be presented in a Segregated manner.

For big scale information, emotions are aroused, influencing decision-making. Thaler's theory was confirmed by the Emotional Index results, indicating that a piece of big positive information and a piece of Small Negative Information result in more positive emotions, while segregating a piece of Big Negative Information and a piece of Small Positive Information results in less negative emotions. These Emotional Index results support hedonic editing from a biometric perspective. Based on Thaler's theory, individuals arrange multiple events, in both financial and non-financial/social domains, either separately or together, in order to maximize positive emotions. (e.g., Linville and Fischer, 1991; Hsee and Leclerc, 1998; Hsee and Zhang, 2004). This investigation demonstrates that a similar effect is observed for Emotional Index as well, with Segregation and Integration showing different valence and arousal for the individual's emotions.

Results from the Approach Withdraw Index and LORETA map show that both the Organization of Information, either Segregation or Integration, and the Order of Information, either Negative-Positive or Positive-Negative, affect a subject's evaluation. With a piece of Big Positive Information and a piece of Small Negative Information, Integration of the two pieces is preferred, which is consistent with Thaler's theory. Further, a recency effect is found when information is integrated, which is consistent with the Belief-adjustment model (Hogarth and Einhorn, 1992) and the recency effect (Tuttle et al., 1997; Pinsker, 2004; Ashton and Ashton, 1988, 1990). These results suggest that subjects reach the highest level of evaluation not only by presentation of an integrated cancellation in gain but also in a Negative-Positive order with the latest positive information providing a higher approach tendency. Similar results were obtained for one piece of Big Negative Information and one piece of Small Positive Information. The interaction of organization and recency suggest a small reduction in loss is preferred to a negative-positive order.

There are limitations to this investigation. First, the sample size is small, especially for the behavioral results and as well future investigations should consider individual variables. Hedonic editing theory often does not consider individual variables, yet the Belief-adjustment model has demonstrated individual psychological factors (e.g., initial beliefs, years of experience) are associated with belief revision effects in accounting (see review by Kahle et al., 2005). Future research should evaluate professional investors and to determine if professionals experience effects similar to non-professionals. Second, further study should consider using real money and using the respondents' own money during the experiments. Real money verse hypothetical payment treatment have been implemented in various laboratorial setting. The phenomenon, known as house money effect, has been observed in some cases. Participants are more risk-seeking and will spend more money when provided with a certain amount of money during the experiment (Cherry et al., 2005; Frino et al., 2008; Chang et al., 2009; Hensher, 2010 p.737). Likewise, decision-making should be evaluated in a variety of areas (e.g., consumer behavior) to identify similar effects and influences.

CONCLUSION

In our paradigm, we considered and tested both the Organization of Information and the Order of Information using both behavioral and neurometric indices. The results are consistent with the Belief-adjustment model in which an individual's investment decision is influenced most by recent information when received in a short-series of mixed information. The neurometric results provide insight into the emotion and tendencies during the judgement procedure. The results suggest that in the scenarios that involve large-scale information, the organization of information (Integration vs. Segregation) influences the emotion and Approach Withdraw tendency, partially consistent with Thaler's hedonic editing theory. Where a big piece of information is involved in the scenario (either BP/SN or BN/SP), emotion is affected by organization in a manner consistent with the predictions of Thaler (1985), such that decreased gain should be presented as integrated, while a small reduction in loss should be presented as segregated. Presenting information in these ways provides for a higher positive emotional value. Moreover, for BP/SN, there is a greater approach potential when two pieces of information are integrated; while in the case of BN/SP, individuals favor the separation of information with the order Negative-Positive. A piece of Big Negative Information followed by a piece of Small Positive Information is the best way to create approach potentials.

The results of this investigation should provide insight for effective communication of information, especially when large-scale information is involved. For the communication of large scale information to individuals or investors, corporations should consider both the order and the organization of the information. Even though the final investment decision may not be different, the individual's emotion and tendency during judgement may be. For a small piece of positive information and a small piece of negative information, it is better to present them in the Negative-Positive order. For a piece of Big Positive Information and a small piece of negative information, it is better to present them in Negative-Positive order and present them Integrated. For a piece of Big Negative Information and a small piece of positive information, it is better to present the Big Negative Information first and the Small Positive Information second.

AUTHOR CONTRIBUTIONS

WY has done majority part of the work, including doing literature review, experiment design, collecting data, analysing the data, interpretation of the result and writing the article. JM came up the main idea of this research and participated in the experiment design and the interpretation of the result. HC assisted in the experiment design and data collection. AM, EM, and DR assisted in data collection and data transfer prior to the analysis. GC assisted in the analyzing the data. MB assisted in preparing the material (translating English materials into Italian and back-translation), interpretation of the the result and provided critical revision. FB assisted in preparing the material (translating English materials into Italian and back-translation) and provided critical revision.

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A Surprising Source of Self-Motivation: Prior Competence Frustration Strengthens One's Motivation to Win in Another Competence-Supportive Activity

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According to self-determination theory (SDT), competence is among the three basic psychological needs essential for one's well-being and optimal functioning, and the frustration of these needs is theoretically predicted to induce a restorative response. While previous studies have explored the restoration process of autonomy and relatedness, empirical evidence for such a process is still lacking for competence. In order to explore this process and to examine the effect of prior competence frustration on one's motivation to win in a subsequent competence-supportive task, we adopted a between-group experimental design and manipulated one's competence frustration through task difficulty in an electrophysiological study. Participants in both groups were instructed to work on the time-estimation task and the stop-watch task in two successive sessions respectively. Participants in the experimental group were asked to complete a highly difficult task in the first session and a task of medium difficulty in the second session, while those in the control group were instructed to work on tasks of medium difficulty in both sessions. In the second session, an enlarged feedback-related negativity (FRN) loss-win difference wave (d-FRN) was observed in the experimental group compared to the control group, indicating that the competence-frustrated participants have an enhanced motivation to win in a subsequent competence-supportive task. Thus, results of the present study provided original neural evidence for the restoration process of frustrated competence, which provided important guidelines for the managerial practice.

Keywords: competence, competence frustration, intrinsic motivation, need restoration, self-determination theory, event-related potentials, feedback-related negativity

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INTRODUCTION

In our daily life, we frequently observe the phenomenon that, instead of being devastated, lots of people will seek an opportunity to prove themselves after a setback. For instance, people who failed an interview may regain confidence and happiness by managing to succeed in other domains (i.e., to win a tennis match). Their behaviors may seem irrational at first glance. After all, winning a tennis match itself would not help them change the interview result. However, this act helps people to restore their undermined perceived competence. This vivid scenario shows that a need restoration process of competence may exist and that individuals may actively enforce self-regulation to fulfill their basic psychological needs.

In order to clarify and integrate varied influencing factors of motivation, psychology and management researchers proposed multiple theories. Among them, self-determination theory (SDT) has emerged as one of the most influential and well-established frameworks of motivation. One major contribution of SDT is that it conceptualizes the three basic psychological needs of autonomy, competence and relatedness as essential and innate for one's psychological growth, internalization and well-being (Deci and Ryan, 2000; Reis et al., 2000). Autonomy reflects one's need to act with a sense of discretion of his/her own behaviors and to feel psychologically self-directed, while relatedness refers to the need to interpersonally connect with others, to give affection, and to receive love and care in return. Finally, competence is defined as the need to feel effective and mastery, and to demonstrate and improve one's abilities (Deci and Ryan, 2000). As a fundamental basic psychological need, the importance of competence satisfaction has been explored in a multitude of fields, such as education, work, health and sports (Milyavskaya and Koestner, 2011). It is widely reported that competence satisfaction is positively correlated with work motivation, job satisfaction, life satisfaction as well as the general well-being (Van den Broeck et al., 2016).

Besides exploring the positive effects of competence satisfaction, recent studies have begun to examine the negative effects of competence frustration. Competence frustration refers to feelings of failure or inadequacy, and doubt over one's own abilities (Bartholomew et al., 2011). When challenges are set too high, negative feedback is provided, and/or the sense of mastery gets undermined by targeted criticism and social comparisons, people would experience competence frustration (Ryan and Deci, 2017). Studies showed that competence frustration is often accompanied by negative outcomes, such as ill-being (Bartholomew et al., 2014), job burnout (Gillet et al., 2015b), counter-productive work behavior (Van den Broeck et al., 2014), cynicism and turnover intentions (Gillet et al., 2015a), disengagement (Jang et al., 2016) and undermined intrinsic motivation (Fang et al., 2017).

Given that experiencing competence satisfaction is crucial to optimal functioning, it is hard to believe that people would passively accept competence frustration without making any defensive reactions. Indeed, previous studies have demonstrated that the frustration of basic psychological needs would lead to a restoration process (Fiske, 2004; Veltkamp et al., 2009). In a recent experimental study, autonomy-frustrated participants were found to pay more attention to autonomy-related stimuli in a subsequent task, which would help them restore undermined autonomy (Radel et al., 2011). Moreover, individuals who experienced autonomy frustration were found to have a greater intrinsic motivation in a subsequent task if this new task gives them a glimpse of autonomy satisfaction (Radel et al., 2014). Besides autonomy, previous studies also reported that individuals who experienced relatedness frustration tried harder and performed better in the next task if this task provided them the opportunity to feel socially accepted (DeWall et al., 2008). However, once people experienced competence frustration, whether they would take actions to restore their perceived competence and be more eager to win in a subsequent competence-supportive task remains elusive. Thus, the aim of this study is to explore the restoration process of competence and to establish the causal relationship between prior competence frustration and one's motivation to win in another activity.

In this experimental study, we adopted a between-subject design. Participants in both groups were instructed to attend two sessions, and they worked on the same task both in session 1 (the time-estimation task, TE) and session 2 (the stop-watch task, SW). In session 1, competence frustration was manipulated by setting different difficulties for the same task, which has been suggested to be a both simple and effective means of competence frustration manipulation (Ryan and Deci, 2017). In session 2, all participants worked on another task of medium difficulty, which was found to be competence-supportive to a great extent (Meng et al., 2016; Ma et al., 2017). In order to examine the effect of prior competence frustration on one' motivation to win in a subsequent competence-supportive task, electrophysiological data of all participants were recorded and analyzed. Specifically, we resorted to feedback-related negativity (FRN), a representative event-related potentials (ERPs) component observed during feedback processing and outcome evaluation to measure one' motivation level (Ma et al., 2014a; Meng and Ma, 2015).

As a negative deflection, FRN generally peaks between 250 ms and 350 ms after feedback onset and is concentrated over the fronto-central electrodes (for a recent literature review, see San Martín, 2012). Source localization studies have demonstrated that the neural generator of the FRN lies in the anterior cingulate cortex (Müller et al., 2005; Bocquillon et al., 2014; Hauser et al., 2014). In order to illustrate the cognitive meaning of FRN, scholars have proposed and developed two mainstream theories, which are reinforcement learning theory and motivational significance theory. According to reinforcement learning theory, FRN is sensitive to the valence of outcome feedback, being more pronounced for negative feedback than for the positive one. The increased FRN amplitude elicited by negative outcomes is resulted from the decreased dopaminergic activity when observing events worse than expected (Holroyd and Coles, 2002). We predicted to replicate the valence effect in this study.

While reinforcement learning theory is helpful in explaining the valence effect of FRN, motivational significance theory takes a difference wave approach and argues that FRN loss-win difference wave (d-FRN) represents the subjective evaluation of the motivational impact of outcome events (Gehring and Willoughby, 2002; Yeung et al., 2005; Masaki et al., 2006). Previous studies have consistently suggested that the d-FRN amplitude reflects the motivational significance of outcomes in both gambling tasks (Masaki et al., 2006; Zhou et al., 2010; Ma et al., 2011) and effort-requiring tasks (Ma et al., 2014b; Meng and Ma, 2015). To be specific, when outcomes in a given experimental condition bear more motivational significance to participants, an enhanced d-FRN would be observed upon feedback (Yeung et al., 2005; Fukushima and Hiraki, 2009; San Martín, 2012; Meng and Ma, 2015). As we hypothesized that individuals who experienced competence frustration beforehand may actively seek to restore their perceived competence in a subsequent less-demanding task, we predicted that they would have a more sustained motivation to win in another competence-supportive task, resulting in a significantly more pronounced d-FRN upon feedback.

It is worth pointing out that, in this study we resort to the d-FRN to measure one's motivation to win rather than intrinsic motivation. Specifically, as we aim to provide direct empirical evidences for the competence restoration process, we examine the effect of prior competence frustration on one's motivation to win (as reflected in the magnitude of d-FRN) in another competence-supportive activity. In previous studies, researchers suggested the d-FRN upon feedback as an electrophysiological indicator of intrinsic motivation (Ma et al., 2014a; Meng and Ma, 2015) either when external rewards are not provided or when monetary incentives are irrelevant to task performances. In this study, as we did not collect subjective ratings on intrinsic motivation from the participants, we cannot be conclusive that the d-FRN reflects intrinsic motivation here. Thus, intrinsic motivation would only be briefly discussed as a possible explanation of the observed d-FRN effect in the "DISCUSSION" section of this article.

Besides establishing a causal link between competence frustration in a prior activity and one's motivation to win in the subsequent competence-supportive one, another aim of this study is to explore effects of personality traits on one' motivation to win during the need restoration process. One personality trait that attracts our attention is achievement goal orientation, which refers to one's beliefs towards the goals they form to succeed, and the driving forces of their learning behaviors (Ames, 1992; Pintrich, 2000; Kaplan and Maehr, 2007). There are two distinct achievement goal orientations. While mastery goal concerns the development of competence and task mastery, performance goal pays attention to the demonstration of one's competence to other people. Each individual has the two orientations at the same time. However, they may vary in levels. Thus, one can be classified as either more mastery-orientated or more performance-orientated. Previous studies consistently reported an undermining effect of performance goal orientation on one's intrinsic motivation (Ryan et al., 1991; Kaplan and Maehr, 2007; Lee, 2010; Barić et al., 2014). Extending this line of studies, in this study we explored whether mastery versus performance goal orientation would affect one's motivation to win (as reflected in the magnitude of d-FRN) in a subsequent less demanding activity after experiencing competence frustration.

MATERIALS AND METHODS

Participants

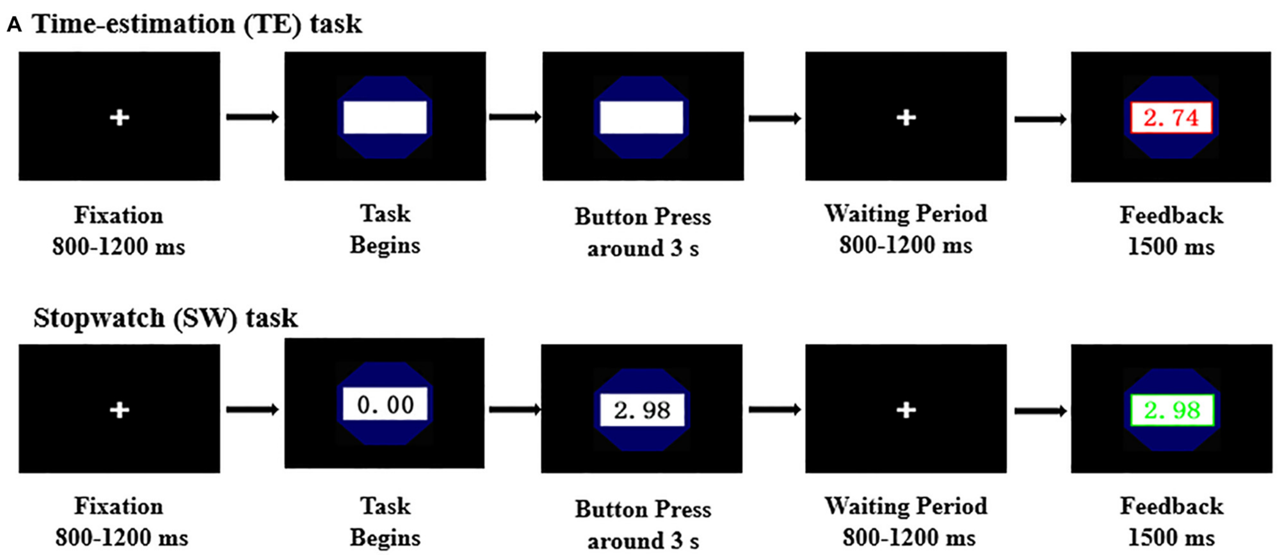
Forty-eight healthy, right-handed participants took part in this study, ranging in age from 19 years to 24 years (M = 19.50, SD = 0.93). A power analysis was conducted to determine the sample size before we started this experiment. We assumed the effect size (f) to be 0.4 and the error probability (α) to be 0.05. The suggested sample size is 44. Thus, our sample size meets the requirement. All participants were randomly assigned to either the control (N = 24, 14 males) or the experimental group (N = 24, 12 males). All participants were registered students from Guangdong University of Technology. They had normal vision after correction and no history of neurological disorders or mental diseases. The study was approved by the Internal Review Board of School of Management, Guangdong University of Technology. All participants provided written informed consent before the experiment formally started.

Stimuli and Procedure

Subjects were comfortably seated in a dimly lit, sound-attenuated and electrically shielded room. Experimental stimuli were presented at the center of a computer screen at a distance of 100 cm, with a visual angle of 6.2° × 5.4°. Subjects were instructed to use a keypad to complete tasks all along. The experiment consisted of two sessions, each containing 60 trials. As illustrated in **Figure 1B**, participants in both groups were instructed to work on the TE task in session 1 and the SW task in session 2, respectively.

In session 1, participants were instructed to accomplish the TE task and to estimate durations of around 3 s. After TE began, participants should respond by pressing any button on the keypad if they considered that the elapsed time was close to 3 s (Meng and Ma, 2015). The closer, the better. In order to manipulate competence frustration between groups in session 1, participants in the control group were instructed to work on a TE task of medium difficulty (the success interval of which is [2.75 s, 3.25 s]), while those in the experimental group were assigned an overwhelmingly difficult TE task (the success interval of which is [2.93 s, 3.07 s]). In session 2, participants from both groups were instructed to complete the same SW task of moderate difficulty (the success interval of which is [2.93 s, 3.07 s]), which is competence-supportive. During the SW game, a SW would automatically start, and participants should try their best to stop the watch around 3 s (Murayama et al., 2010; Albrecht et al., 2014; Ma et al., 2014a, 2017; Meng et al., 2016). Again, the closer, the better. All these time windows were determined by a pilot study conducted before the formal experiment, which ensured that typical participants would succeed in around 15% and 50% trials when working on the overwhelmingly difficult task and the task of medium difficulty respectively. It is worth pointing out that in order to prevent any confounds, participants were only told that the whole experiment would be divided by two sessions, and they were introduced the specific task immediately before the corresponding session began.

As demonstrated in **Figure 1A**, each trial commenced with a cross symbol that lasted for 800–1200 ms. After the task began, participants may press any button they like on the keypad to complete the task. Following the button press, a fixation period that lasted for 800–1200 ms was demonstrated. By the end of a trial, participants would receive their performance feedback for 1500 ms. If the response was close enough to the target, which



B

Group	Session 1	Session 2
Control group	60 trials of the TE task (medium difficulty)	60 trials of the SW task (medium difficulty)
Experimental group	60 trials of the TE task (high difficulty)	60 trials of the SW task (medium difficulty)

FIGURE 1 | The experimental paradigm. **(A)** Illustration of time-estimation (TE) and stopwatch (SW) tasks. **(B)** Demonstration of the experimental procedure.

fell into the pre-determined interval, task performances would be displayed in a green font and with a green border. However, if the behavioral response occurred outside of the pre-defined success interval, task performances would be displayed in a red font corresponding with the red border instead. There was a randomized blank interval that lasted for 600–1000 ms before the next trial started.

All subjects were required to complete an online questionnaire through a professional survey website before the experiment was implemented. The scale developed by Button was adopted to evaluate the achievement goal orientation of candidate participants (Button et al., 1996). The questionnaire on achievement goal orientation is included in **Supplementary Table S2**. Odd number items measure one's performance goal orientation, while even number items measure one's mastery goal orientation. The Cronbach's α of the sub-scales for performance goal orientation and mastery goal orientation are 0.692 and 0.771, respectively. At the end of the experiment, participants were asked to rate their competence frustration level when working on the TE task. We measured one' perception of competence frustration by adapting the basic psychological need satisfaction and frustration scale—work domain (Chen et al., 2015; Schultz et al., 2015), which is shown in **Supplementary Table S1**. The Cronbach's α of this scale is 0.815. It is worth pointing out that, for all these scales, participants were asked to rate on a 7-point scale ranging from 1 (Do not fully agree) to 7 (Totally agree). Before the experiment formally started, subjects were told that they would receive ¥40 as compensation for their participation. Thus, their task performances were irrelevant to the final payments. To familiarize them with the tasks, a practice session adopting the formal task was implemented before the start of each session. After the experiment, subjects were debriefed and paid. Stimuli, recording triggers and response data were presented and recorded by E-Prime 2.0 (Psychology Software Tools, Pittsburgh, PA, USA).

EEG Data Recordings and Analyses

The electroencephalogram (EEG) was recorded with the eego amplifier, using a Waveguard EEG Cap with 64 Ag/AgCl electrodes mounted according to the extended international 10–20 system (both manufactured by ANT Neuro, Enschede, Netherlands). Channel data were online band-pass-filtered from 0.1 Hz to 100 Hz and recorded at a sampling rate of 500 Hz. The left mastoid served as the on-line reference, and the EEG was off-line re-referenced to the mathematically averaged mastoids. Impedances were kept below 10 kΩ throughout the experiment. During off-line data analyses, EEG data were pre-processed adopting ASALab 4.10.1 (ANT Neuro, Enschede, Netherlands). Ocular artifacts were identified and corrected with the eye movement correction algorithm embedded in the ASALab program. The EEGs went through a digital low-pass filter at 30 Hz (24 dB/octave). For the FRN, time windows of 200 ms before and 800 ms after onset of the feedback were segmented, with the activity from −200 ms to 0 ms serving as the baseline. For each participant, the recorded EEGs over each recording site were averaged across each experimental condition. Trials containing amplifier clipping, bursts of electromyography activity, or peak-to-peak deflection that exceeded ±100 μV were excluded from the final averaging.

In this study, we decide to focus our analysis on a specific electrode cluster. While a pre-selection of electrodes might be reductionist, which does not provide much information on possible spatial differences during cognitive processing, this is a common practice for ERP studies, especially for those that focused on well-studied ERP components such as the FRN. As has been discussed in the introduction, the FRN is a negative deflection observed primarily at the fronto-central electrodes, which generally reaches its maximum magnitude around 300 ms after feedback onset (Nieuwenhuis et al., 2004; Torres et al., 2013). In most of the previous studies, FRN was measured at FCz (Oemisch et al., 2017; Fernandes et al., 2018), Fz and FCz (Megías et al., 2018), Fz, FCz and Cz (Hird et al., 2017), or Fz, Cz and Pz (Cohen et al., 2007). It was generally quantified as the mean amplitude in a chosen time window (Cohen et al., 2007; Hird et al., 2017; Fernandes et al., 2018; Megías et al., 2018). Recently, as one of the most famous EEG experts, Luck suggested that for classical ERP components such as the FRN, including electrode as a factor does not provide much useful information while may hide some significant results (Luck and Gaspelin, 2017). Following this suggestion, we selected an electrode cluster (FC1, FCz, FC2) for the FRN analysis based on grand averaged waveforms and its anterior distribution in this study. As the most negative peak of the FRN appeared around 245 ms after feedback onset, we used the mean amplitudes in the time window of 210–280 ms following feedback onset in a 2 (group) × 2 (outcome) repeated measure ANOVAs. The Greenhouse-Geisser correction for repeated measures was applied when necessary. While it might be interesting to test a possible mediation effect of competence frustration between our experimental manipulation of task difficulty and the d-FRN amplitude, this test was not conducted in this study. A major reason is that a typical mediation analysis requires a minimum number of participants, while most electrophysiological studies (including this one) fail to satisfy this requirement. An independent *t*-test was adopted in behavioral analyses. Specifically, to compare the mean error between the two groups, the mean absolute deviation around the central point (3 s) was calculated.

RESULTS

Behavioral Results

The independent sample *t*-test showed that there was a significant difference in success rates ($M_{experimental}$ = 0.16 (SD = 0.055), $M_{control}$ = 0.55 (SD = 0.147); $t_{(46)}$= 12.431, $p < 0.001$, cohen'd = 3.51) in the TE task during session 1. In addition, the level of competence frustration was significantly different between the control group and the experimental group ($M_{experimental}$ = 4.625 (SD = 0.944), $M_{control}$ = 3.052 (SD = 1.249); $t_{(46)}$= −4.922, $p < 0.001$, cohen'd = 1.42), which confirmed that our manipulation was successful. For performance in the SW task during session 2, there were no significant differences in success rates ($M_{experimental}$ = 0.500 (SD = 0.127), $M_{control}$ = 0.484 (SD = 0.131); $t_{(46)}$= 0.429, $p = 0.483$, cohen'd = 0.12) or mean error ($M_{experimental}$ = 0.097 (SD = 0.035), $M_{control}$ = 0.098 (SD = 0.031); $t_{(38)}$ = −0.057, $p = 0.973$, cohen'd = 0.03) between the two groups. Meanwhile, independent sample *t*-test results indicated that there were no significant differences in one's mastery goal orientation ($M_{experimental}$ = 5.854 (SD = 0.773), $M_{control}$ = 5.819 (SD = 0.832); $t_{(46)}$= −0.150, $p = 0.713$, cohen'd = 0.04) or performance goal orientation ($M_{experimental}$ = 5.063 (SD = 0.887), $M_{control}$ = 5.146 (SD = 0.893); $t_{(46)}$= 0.324, $p = 0.673$, cohen'd = 0.12) between the two groups.

ERP Results

After EEG data processing, the averaged trial numbers are M_{win} = 27.62 (SD_{win} = 7.44) and M_{lose} = 26.71 (SD_{lose} = 6.78) in the control group, while are M_{win} = 28.52 (SD_{win} = 8.88) and M_{lose} = 27.42 (SD_{lose} = 8.49) in the experimental group, which are comparable to each other. As demonstrated in **Figure 2**, the mean FRN amplitudes were 12.998 μV (experimental group-win), 8.592 μV (experimental group-lose), 10.608 μV (control group-win) and 8.492 μV (control group-lose) in respective conditions. An ANOVA analysis for the FRN showed a significant main effect of outcome ($F_{(1,46)} = 50.605$; $p < 0.001$; $\eta^2 = 0.524$). However, the main effect of group was not significant ($F_{(1,46)} = 0.614$; $p = 0.437$; $\eta^2 = 0.013$). The main effect of outcome indicated that there was a more negative FRN in the losing condition than in the winning condition. In addition, the significant interaction effect between group and outcome ($F_{(1,46)} = 6.243$; $p = 0.016$; $\eta^2 = 0.119$) indicated that the d-FRN amplitude in the experimental group (−4.406 μV) was more pronounced compared with that in the control group (−2.115 μV). Because of the significant interaction effect between outcome and group, simple effect analyses were subsequently conducted. Negative feedback was found to elicit a more negative deflection than the positive one in both experimental ($F_{(1,23)} = 37.645$; $p < 0.001$; $\eta^2 = 0.621$) and control groups ($F_{(1,23)} = 13.781.538$; $p < 0.01$; $\eta^2 = 0.375$). Meanwhile, no significant between-group differences were observed either when positive feedback ($F_{(1,46)} = 1.855$; $p = 0.18$; $\eta^2 = 0.039$) or negative feedback ($F_{(1,46)} = 0.004$; $p = 0.949$; $\eta^2 = 0.001$) was provided.

Combining behavioral and electrophysiological data, we found that one's competence frustration negatively correlated with the mean d-FRN amplitude ($r = −0.312$, $p = 0.031$), while one's performance goal orientation positively correlated with the mean d-FRN amplitude ($r = 0.457$, $p < 0.01$). To be specific, while performance goal orientation significantly correlated with the mean d-FRN amplitude in the experimental group ($r = 0.591$,

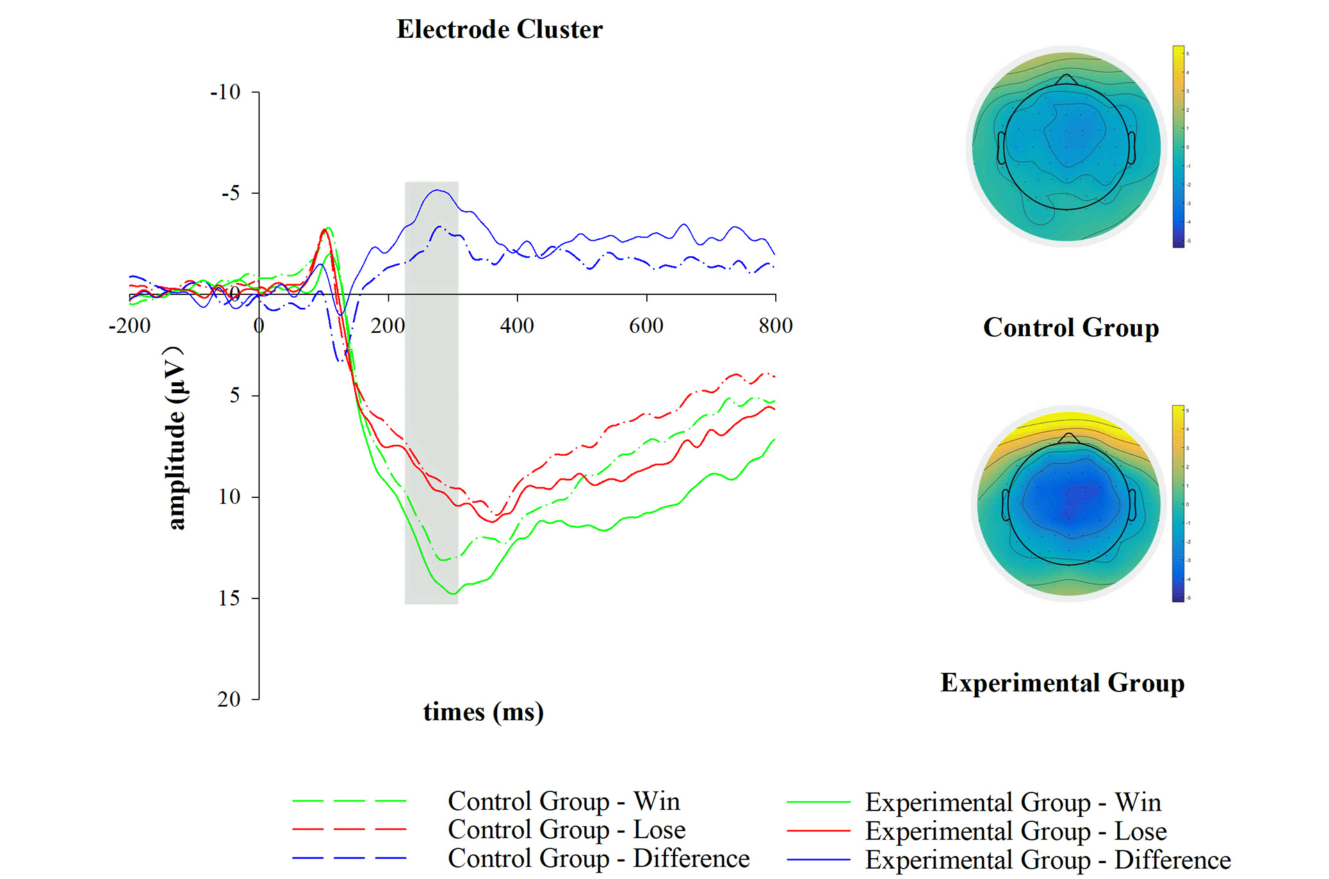


FIGURE 2 | Feedback-related negativity (FRN) results during the outcome appraisal stage. For illustration, grand-averaged event-related potential (ERP) waveforms of FRN and FRN loss-win difference wave (d-FRN) from the electrode cluster (FC1, FCz, FC2) are shown for group (control group versus experimental group) and outcome (win versus lose) conditions. The scalp topographic distribution of d-FRN is provided for control and experimental groups, and the bar for the topographic map ranges from -5 μV to 5 μV.

$p < 0.01$), we did not find such a relationship in participants of the control group ($r = 0.326$, $p = 0.120$). There was no significant correlation between one's mastery goal orientation and the mean d-FRN amplitude ($r = 0.020$, $p = 0.895$) in this study.

DISCUSSION

The Restoration Process of Frustrated Competence

According to SDT, the satisfaction of each basic psychological need is fundamental for the maintenance of one's optimal functioning and well-being (Deci and Ryan, 2000). Recent evidences suggested that, in response to need frustration, individuals may take active actions to restore it through self-regulation (Fiske, 2004; Veltkamp et al., 2009). In line with this reasoning, a number of studies conducted by Radel et al. (2011, 2013, 2014) have explored the effect of prior autonomy frustration on one's motivation, attention and decision-making in a subsequent activity if their perceived autonomy can get restored in it. Moreover, a few pioneering studies have explored the relatedness restoration process and the effect of prior relatedness frustration on one's subsequent behaviors (Gardner et al., 2000; Pickett et al., 2004; DeWall et al., 2008). As a comparison, few (if any) studies have examined the restoration process of competence. To fill this research gap, in a recent field study conducted in the educational setting, we revealed a potentially positive effect of competence frustration outside of its primary thwarting context (Fang et al., 2017). Extending our previous study, we adopted a between-subjects design and directly manipulated one' competence frustration in this experimental study. The EEGs of our participants were recorded all along, which makes it possible for us to examine the effect of prior competence frustration on one's motivation to win in a subsequent competence-supportive activity.

This experiment consisted of two sessions, and participants in both the experimental group and the control group were instructed to work on the TE task in session 1 and the SW task in session 2. According to the theoretical reasoning of the need restoration process, once a basic psychological need gets frustrated, one would actively take part in another activity and get immersed in it if this activity can restore his/her frustrated need (Radel et al., 2013). It is fundamental for the second activity to be different from the original one, as it would be very difficult for one to restore their frustrated need in the same activity, even if this activity becomes more need-supportive than before (Radel et al., 2013). Accordingly, to create an opportunity for competence restoration, we adopted different tasks in different sessions. In this study, competence frustration was manipulated through task difficulty. Thus, while participants in both groups worked on the TE task in session 1, participants in the experimental group were faced with an overwhelmingly difficult TE task. To give them the opportunity to restore their competence in session 2, the SW task was set as moderately difficult, which is competence-supportive (Ma et al., 2017). As a control, those in the control group worked on moderately difficult tasks in both sessions.

Previous literatures consistently showed that the FRN loomed larger in response to the negative feedback compared with the positive one (San Martín, 2012). Accordingly, we found the valence effect on the magnitude of the FRN in both the experimental and the control group. The key finding of this study is that participants in the experimental group showed an enlarged d-FRN toward feedback outcomes compared with those in the control group. In the pioneering study that proposed the motivational significance account of FRN, Gehring applied a binary choice gambling task in which subjects were asked to choose between 5 and 25, which would lead to either a gain or a loss of the corresponding amount of money. When choosing 25, outcomes of the gambling task bear more motivational significance to the participants. A larger d-FRN was observed when participants chose 25 instead of 5. Based on this discovery, Gehring and Willoughby (2002) argued that the amplitude of d-FRN may reflect one's motivation level in terms of outcome evaluation. Similar findings were reported in effort-requiring tasks, as the mere confirmative action (Zhou et al., 2010), the additional effort put into a task (Ma et al., 2014b), as well as the opportunity to choose between equally difficult tasks (Meng and Ma, 2015) all resulted in a greater motivation to win and contributed to the enhanced d-FRN upon feedback. To sum up, a growing number of studies have demonstrated that FRN is a reflection of the motivational impact on the processing of outcome stimuli (Gehring and Willoughby, 2002; Yeung et al., 2005; Masaki et al., 2006; Zhou et al., 2010). In the current study, we observed a more pronounced d-FRN in the experimental group during session 2. In line with the motivational significance theory of FRN, this finding suggested that prior competence frustration strengthened one's motivation to win in a subsequent less-demanding task, which provided empirical evidence for the competence restoration process.

d-FRN as a Tentative Neural Indicator of Intrinsic Motivation

Intrinsic motivation refers to one's spontaneous potential to be curious and interested, to look for challenges and cultivate their skills and knowledge in the absence of external rewards (Deci and Ryan, 2000). In recent years, a number of pioneering studies have explored the neural underpinnings of intrinsic motivation (Murayama et al., 2010; Albrecht et al., 2014; DePasque and Tricomi, 2015; Marsden et al., 2015; Meng and Ma, 2015). According to recent literature reviews on the progress of neuroscientific investigations of intrinsic motivation, when participating in intrinsically motivated activities, individuals' dopaminergic value system would be responsive to cues that signal task-related progress (Di Domenico and Ryan, 2017; Reeve and Lee, 2018). To be specific, as the anterior striatum has been well established to be responsible for the processing of feedback information (Tricomi et al., 2006; DePasque and Tricomi, 2015), most researchers who applied the functional magnetic resonance imaging (fMRI) technique resorted to the blood oxygen-level dependent (BOLD) signal in the anterior striatum during outcome evaluation to measure one' intrinsic motivation (Murayama et al., 2010; DePasque and Tricomi, 2015). In a similar manner, researchers who adopted an electrophysiological approach focused on one's neural responses to success and failure feedbacks in effort tasks and adopted the d-FRN to measure one's intrinsic motivation (Ma et al., 2014a; Meng and Ma, 2015).

In the first electrophysiological study that examined intrinsic motivation, the researchers modified the experimental paradigm of Murayama et al. (2010) to explore the crowding out effect of monetary incentives on one's intrinsic motivation (Ma et al., 2014a). They discovered that the d-FRN toward inherent lose-win divergence was significantly reduced if extrinsic rewards were once given but no longer available in the experimental group. However, this phenomenon was not observed in the control group (Ma et al., 2014a). In another study that explored the relationship between autonomy satisfaction and intrinsic motivation, the researchers manipulated the opportunity to choose between equally difficult tasks, and participants received a fixed payment irrelevant to their task performances. It was found that satisfaction of autonomy through the provision of choices brought a prominently more negative d-FRN toward performance feedback (Meng and Ma, 2015). In these two studies, performance feedback is unrelated with monetary rewards, and participants are assumed to complete experimental tasks purely out of intrinsic motivation. As the motivational significance theory indicated the magnitude of d-FRN to reflect one's motivation level, the researchers went a step further to suggest d-FRN as a candidate neural indicator of intrinsic motivation (Ma et al., 2014a; Meng and Ma, 2015).

In our experiment, subjects received a fixed payment irrelated with task performances. We observed a more pronounced d-FRN in the experimental group compared with the control group during session 2. In support of this group-level finding, we also found that competence frustration negatively correlated with the d-FRN amplitude in session 2. If d-FRN can be regarded as a neural index of intrinsic motivation, these findings would help establish the causal relationship between prior competence frustration and one's strengthened intrinsic motivation in another competence-supportive activity. When conducting this study, we did not ask participants to rate their intrinsic motivation and perceived competence in session 2. A major reason is that we did not want to make our research content explicit to the participants. If they realized what we were trying to examine when filling the scales, their responses to the items might be biased. At present, as self-reported intrinsic motivation data supportive of the electrophysiological findings were not collected, we refrain from being conclusive and suggest this mechanism to be only a speculation. This might be a limitation of this study, and follow-up studies are highly welcome.

IMPLICATIONS AND FUTURE DIRECTIONS

Findings of this study contribute to the need restoration hypothesis built on SDT, according to which the frustration of basic psychological needs would lead to a restoration process (Fiske, 2004; Veltkamp et al., 2009). To date, studies have explored some need restoration processes activated by need frustration. For instance, converging evidences showed that individuals would take actions to regain relatedness by becoming more attentive to social information (Gardner et al., 2000), nonverbal social cues (Pickett et al., 2004) and signs of acceptance (DeWall et al., 2008) after experiencing relatedness frustration. Moreover, going through relatedness frustration increased one's motivation to renew affiliative bonds with others (DeWall et al., 2008). Besides autonomy and relatedness, the existence of a restoration process of competence has been recently tested as well. In a pioneering field study conducted in an educational setting, we found that for students who had been competence-frustrated to a great extent in a preceding course, a restoration process would be activated if the current course can help restore their competence, as they showed enhanced intrinsic motivation in the current course (Fang et al., 2017). While findings of our previous field study are illuminating, we cannot establish a causal relationship between one's competence frustration in a previous activity and need-restorative behaviors in the current activity. In this study, competence frustration was directly manipulated, which is among the very first experimental studies that directly examine the competence need restoration process. Our results further confirmed the need restoration hypothesis, as competence-frustrated participants were found to restore their competence through enhancing the motivation to win in a subsequent less-demanding task.

It is worth noting that, in this study, one's behavioral response toward competence frustration was only examined during its early stage. Thus, whether a similar restoration process will still be activated once an individual endure consistent competence frustration remains to be examined. Previous studies on relatedness frustration suggested that if one remained relatedness-frustrated for a long period of time and did not have the opportunity to restore relatedness, they may compensate by becoming more aggressive (Twenge et al., 2001), less altruistic toward others (Twenge et al., 2007), or accepting passivity and perceiving worthlessness (Williams, 2009). While our results suggested that prior competence frustration may affect one's motivation to win in subsequent competence-supportive activities, it is possible that one may not get the opportunity to restore competence in the short run and certain detrimental effects of competence frustration may last long. Thus, follow-up studies may consider examining the consequences of long-term suffering of competence frustration. The evolution of one's need restoration strategy and behavioral responses over time may also be explored in future studies.

Another theoretical contribution of this study is that we provided preliminary electrophysiological evidence for achievement goal orientation theory. In our study, results from correlation analyses between personality traits and the d-FRN observed in session 2 showed that one's performance goal orientation negatively correlated with the motivation to win (as a more negative d-FRN has been proposed to suggest an enhanced motivation to win). This finding held true for the experimental group only. Thus, among the participants whose competence got frustrated, those who normally care about task performances rather than task mastery would pay less attention to task performances and show attenuated motivation afterwards. This finding suggested that following competence frustration, performance goal orientation may impact one's motivation level in a subsequent less demanding activity. In other words, while the competence restoration process might be common, there are individual differences concerning its intensity. If d-FRN can be seen as a neural indicator of intrinsic motivation, then results of this study are consistent with some theorists' statement that the pursuit of performance goals has a negative effect on intrinsic motivation (Ryan et al., 1991; Kaplan and Maehr, 2007; Lee, 2010; Barić et al., 2014). Interestingly, we did not find a significant correlation between mastery goal orientation and the mean amplitude of d-FRN in session 2.

Findings of this study also provide important guidelines for the managerial practice. To begin with, as we found that individuals would take active actions to restore their competence after it had been frustrated, managers of enterprises should endeavor to protect competence of their employees, which is fundamental to their overall well-being. For instance, when the work is too demanding or challenging, managers may pay attention to giving timely positive feedback or providing moderate autonomy to the employees (Meng and Ma, 2015; Meng and Yang, 2018). Our findings also bear practical implications for work arrangement. In this study, we found a surprising source of self-motivation, as competence-frustrated individuals would activate a need-restorative process and show enhanced motivation in a subsequent competence-supportive activity. This is not to suggest that managers should deliberately undermine the perceived competence of their employees so as to motivate them later on. After all, according to predictions of SDT, one's motivation would be threatened in the activity which frustrated their competence (Deci and Ryan, 2000; Ryan and Deci, 2017). Rather, we urge the managers to take advantage of the need restoration process. In the workplace, some work is inevitably demanding, and it is highly likely that competence of some employees would get frustrated. If this already happened, managers should try to guarantee that this work is to be followed by a comparatively simple one. This arrangement gives employees the opportunity to regain competence, and they would get immersed in their jobs. To conclude, reasonable work arrangement can intrigue employees' work motivation and thus boost enterprise performances.

CONCLUSION

In an experimental study, we manipulated task difficulty to explore the effect of prior competence frustration on one's motivation to win in another competence-supportive activity. Electrophysiological evidences suggested that participants who experienced competence frustration beforehand would increase their motivation to win (as reflected in the magnitude of d-FRN) in a subsequent task if it could help restore competence, which provided direct empirical evidences for the competence restoration hypothesis built on SDT and important guidelines for the managerial practice. Thus, by examining effects of competence frustration outside of its primary thwarting context, we complement and extend existing findings on the dynamics between need frustration and one's (intrinsic) motivation.

AUTHOR CONTRIBUTIONS

LM and HF conceived and designed the study. HF collected and analyzed the data. HF and LM interpreted the data and drafted the manuscript. LM, HF, BH, HjF, HjZ and ZM reviewed and edited the manuscript. LM administered the project.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fnhum.2018.00314/full#supplementary-material

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"You Win, You Buy"—How Continuous Win Effect Influence Consumers' Price Perception: An ERP Study

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Price played an important role in most purchases. Buying behavior was strongly determined by consumers' price expectations. Emotion as a research hotspot was demonstrated to be ubiquitous in marketing and influenced purchase processing as well. This study addressed interests upon whether emotion arousal would influence consumers' price perceptions and their willingness to purchase. Compared to such emotion researches which normally adopted emotional pictures as priming stimuli, we creatively employed a two-player "Finger Play" (FP) game without monetary gains or losses to arouse subjects' emotion in the experiment. A 2 (FP Game Results: Continuous Win vs. Continuous Lose) by 2 (Price Conditions: High Price vs. Low Price) Event-Related Potentials (ERPs) experiment was designed to investigate whether game results would arouse different emotions and influence subjects' perception of product price. Both behavioral and ERP results indicated that subjects' price perception was deeply impacted by emotions induced from continuous win/lose experiences.

Keywords: continuous win effect, price perception, event-related potentials, P2, P300, LPP, neuromanagement, neuromarketing

INTRODUCTION

Price played an important role in most purchases. Buying behavior was strongly determined by consumers' price expectations and the extent to which real prices violated those expectations (Schaefer et al., 2016). The ratio and trade-off between quality and price constituted a value-for-money conceptualization (Carvens et al., 1988; Monroe, 1990; Sweeney and Soutar, 2001). Normally, customers mostly avoided excessive prices products in addition to those deeply preferred ones (Knutson et al., 2007) and their expectations of higher quality at higher prices could be self-fulfilled if sellers did not charge higher prices for lower quality products (Gerstner, 1985). According to Gerstner (1985), consumer might understand the demand-related quality information or supply-related quality information of products through price (Gerstner, 1985). Having insight into of consumers' price perception and the influence factors during the purchase process became an important research emphasis of marketers and academicians.

Distinct components of the individuals' purchase decision processes might be difficultly separated and characterized by conventional research methods, while neuroscience and neuromanagement methods offered the hope (Knutson et al., 2007). Researches of consumer neuroscience draw heavily on the extant literatures in multiple areas since the very first published consumer neuroscience article which discussed how brand affected the experience of consumption (McClure et al., 2004; Smidts et al., 2014). Most works paid attention to products and price, as well as brands (Knutson et al., 2007; Plassmann et al., 2008, 2012; Smidts et al., 2014). For example, Knutson et al. (2007) investigated neural predictors of purchase processing and indicated that 'excessive prices activated the insula and deactivated the mesial prefrontal cortex (MPFC) prior to the purchase decision' using fMRI technology. Karmarkar et al. (2015) examined the sequence-dependent effects of price and product information on decision-making process using fMRI methods and suggested that price primacy highlighted considerations of product worth, and could thereby influence purchasing in conclusion (Sacré et al., 2016).

Some academicians draw their research interests on the relevance of emotion and marketing in the studies of perspective of cognitive science and consumer neuroscience (Mick and Fournier, 1998; Shiv and Fedorikhin, 1999; Chaudhuri and Holbrook, 2001; Belk et al., 2003; Henning-Thurau et al., 2006; Yan et al., 2018). Emotion was ubiquitous in marketing and influenced purchase processing, measured effects of marketing-mix tactics, as well as consumer welfare (Baogozzi et al., 1999). Neuroscientists also illustrated that decision making involved not only the cold-hearted calculation of expected utility but also more subtle and sometimes depending critically upon emotion (Shiv and Fedorikhin, 1999). The significant advances in the study of emotion and decision making had been seen obviously (Shiv, 2007). Advances had occurred in the study of task-induced affect, integral affect, and anticipatory affect as well (Luce, 1998; Shiv and Nowlis, 2004; Nowlis and Shiv, 2005).

Studies on emotion were mainly carried out in the following three aspects: emotion valence (unpleasant-to-pleasant), emotional arousal (low-to-high), and paradigms to evoke emotional process. Most affective ERP researches adopted stimuli from the International Affective Picture System (IAPS) which contains pictures rated with valence category (pleasant and unpleasant) and arousal level (low to high) on a nine-point scale (Lang et al., 1999; Olofsson et al., 2008). Neural imaging studies further demonstrated the separate attributes of emotion as positive and negative (Grodd et al., 1995; Schneider et al., 1997). Lifshitz (1966) found that pleasant and unpleasant pictures induced a positive-going waveform at about 350–450 ms after stimulus onset compared to neutral ones back in the sixty's of twentieth century (Lifshitz, 1966). Schupp et al. (2000) also indicated larger late positive potentials (LPP) elicited when subjects saw pleasant and unpleasant pictures rather than neutral ones. Additionally, the latter portion of ERP waveform LPP indicated elevated positivity to high-arousing stimulation (Cuthbert et al., 2000).

Normally, most people love to win and hate to lose when they play a game. Some findings of psychological and mental researches explained the phenomenon by considering winning as a reward while losing as a punishment for people (Robbins and Everitt, 2007; Salamone et al., 2007; Tomer et al., 2014). Humans constantly chose actions based on the balance between the desire for pleasure and aversion to punishment (Tomer et al., 2014). Many of the researches on winning and losing concentrated upon competitions or gambling games and pointed out that winning or losing would influence a wide range of social and personal behaviors (Elliot and Covington, 2001; Smith et al., 2009; Zysberg and Kimhi, 2013; Doron and Gaudreau, 2014; Dugatkin and Reeve, 2014; Smidts et al., 2014; Xu and Harvey, 2014; Sacré et al., 2016). The neural activity modulated significantly between win and lose trials in the anterior insula and gamma-band activity increased around 500 ms after the show computer cards for win trials (Sacré et al., 2016). Yeung et al.'s research Yeung and Sanfey (2004) examined the properties of P300 and feedback negativity components which were unpredictably associated with monetary gains and losses of variable magnitude in a simple gambling game. According to their findings, P300 was sensitivity to the reward value of alternative, non-selected stimuli. The two-factor theory of emotion explained the process of human emotional awakening (Schachter and Singer, 1962; Burns and Corpus, 2004) and suggested that a deviant situation such as a winning or losing streak in sports games had the potential to regulate the human's emotional state or choice behavior (Ayton and Fischer, 2004; Attali, 2013).

This study addressed interests on the role of emotion in consumers' price perception. Since winning or losing might make people have positive or negative feelings (pleasant vs. unpleasant), whether a competitive game could be adopted as the emotional priming paradigm instead of affective pictures to do the investigation. With our best knowledge and in order to strengthen subjects' sense of presence and authenticity, we creatively applied a two-player simple game—"Finger Play" (FP) known by nearly everyone involved no monetary gains or losses as the emotion priming stimuli, resulting a 2 (FP Game Results: Continuous Win vs. Continuous Lose) by 2 (Price Levels: High Price vs. Low Price) event-related potentials (ERPs) experiment designed to explore two research issues: (1) whether game results without monetary gain/loss would arouse subjects' different emotions; (2) If it would be, how the emotions impact subjects' perception of product price and their buying behavior. After the ERP experiment, participants were asked to rank a preference score of products chosen for this study to confirm that conditions of products attributes were controlled.

MATERIALS AND METHODS

Participants

Twenty-six healthy, right-handed students (nine female) recruited at Zhejiang University participated in this study, age from 19 to 27 years (*Mean* = 22.07 years, *SD* = 1.9 years). All subjects were native Chinese speakers, had normal or corrected-to-normal vision, and did not have any history of neurological disorders or mental diseases. This study was approved by the Neuromanagement Laboratory Ethics Committee at Zhejiang University. Informed consents were obtained from subjects prior to the formal experiments. Data from three subjects were discarded for excessive recording artifacts, resulting 23 (eight female) valid subjects (aged 19–27 years, *Mean* = 22.04 years, *SD* = 1.92 years) were included in the final data analysis.

Stimulus Material

Sixty hard-disc pictures which had same color and similar shape were used in this study. All the pictures were obtained from the Internet and the brands were erased. In ERP experiment, two groups of random number were generated from Excel of Windows Office 2007 and each hard-disc picture was paired with a high price set (from 500 to 700 RMB) and a low price set (from 200 to 400 RMB). Product pictures were equally and randomly divided into four groups, group 1 had 15 pictures corresponded with continuous win situation, group 2 also had 15 pictures corresponded with continuous lose situation, group 3 and group 4 had 30 pictures linked to other situations (e.g., two draws/one win-one draw/one lose-one draw etc.). Each product picture was paired with two prices (high price vs. low price), resulting doubled the number of total pictures. Every product picture with price presented twice and in a random sequence during the whole experiment. In preference rating experiment, same pictures used in ERP experiment were obtained, however, price information was erased in each picture. All the pictures were adjusted to a uniform size (10 by 11 cm, 300 by 332 pixels) and gray-processed by Photoshop software to ensure consistency in the background, brightness, contrast and color.

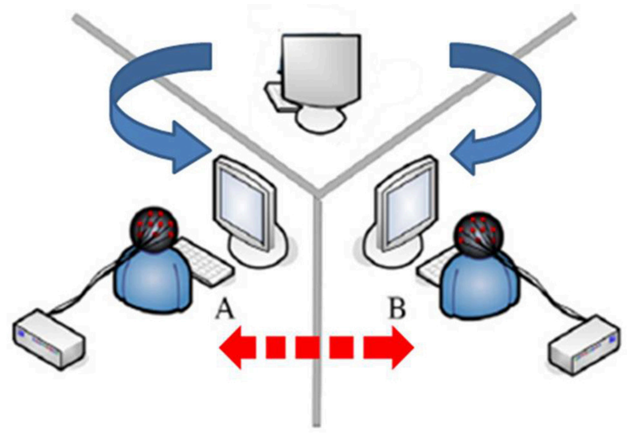

FIGURE 1 | Experimental schematic diagram. Two participants joined in the ERP experiment. They met firstly and were informed to play FP game with each other before entering in the different rooms. Two experimenters started the experimental program together with a 3 beats countdown. Participants actually play the game with the computer programs.

Experiment Procedure

Experiment instruction was shown to participants on paper handouts at the very beginning. Subjects were seated comfortably in a dimly lit, sound-attenuated and electrically shielded room. Experimental stimuli were presented centrally on a computer screen at a distance of 100 cm from each subjects' face. A keypad was provided to the participants to make their choices. Each subject had three practice trials to become familiar with the experimental procedure before the formal experiment.

In order to construct subjects' sense of presence and authenticity, we referred to the experiment schematic diagram of Ma et al. (2011) with some changes on the basis of our study purposes (see **Figure 1**). In their research, three persons (two friends and one stranger) were recruited at once to do a gamble task together and evaluated their empathic responses to others' gains or losses (Ma et al., 2011); in our research, two subjects (strangers) were recruited at once and they did the ERP experiment in different rooms at the same time. All subjects were informed that they planned to buy a hard-disc on a shopping website. The shape, quality, function and color of these hard-discs were no significant differences; the only different information was the price. They were required to decide whether to add a hard-disc to cart in every trial, however, they did not need to actually buy it in the end. Moreover, we simulated the FP game as an online interactive activity developed by the shopping website before they browsed the products. All participants were informed that if they played the FP game, they would receive a coupon for shopping next time. Further, in our experiment, every two-participant was told that they were the randomly paired customers to play the game together before they searched the hard-disc. To be worth mentioning, the game results were actually operated by the computer program (wrote by E-Prime 2.0) to confirm that there would be sufficient effective trials for each condition. From an ethical perspective, all participants were informed that they actually played the game with computer program in the end of the experiment.

Figure 2 indicates a single trial of ERP experiment. First, a randomly 400–600 ms fixation appeared on a gray screen. Then, the FP frame presented until the end of subjects' choice (key 1 and 3 to move the arrow, key 2 to confirm the choice; the rules of FP: scissors > paper > stone > scissors). The game result showed for 1,000 ms after a randomly blank (400–600 ms). After two turns of the game, a hard-disc picture with high or low price continuously presented after another randomly 400–600 ms blank and lasted 1,000 ms. Participants subsequently made their decision whether adding this hard-disc to cart or not with a provided keypad (key 1 = add to cart, key 3 = not add to cart; half subjects pressed key 3 to add and key 1 to exit). A 1,000 ms blank showed at the end of each trial.

There were two blocks in this experiment, every subject had 180 trials (90 trials for each block) in total [include 60 trials of continuous win situation (30 for high price products and 30 for low price products), 60 trials of continuous lose situation and 60 trials of other situations]. Participants took a rest about 3–5 min during the two blocks.

When subjects finished the ERP experiment, they would have a 10 min rest. After the rest, all participants were asked to do the preference rating experiment (see **Figure 3**).

Figure 3 showed the procedure of the preference rating experiment. FP was removed and hard-disc pictures without price information were presented directly. A randomly 400–600 ms fixation came first, then the hard-disc picture was onset for 1,000 ms, participants used a provided keypad to rank their preference degree of the product (key 1 and 3 to move the arrow, key 2 to confirm the preference score). Likert scale with 5 points (from 1 = "not like it at all" to 5 = "extremely like it") was used as rating method. Each hard-disc pictures randomly appeared twice in this experiment, resulting 120 trials in total.

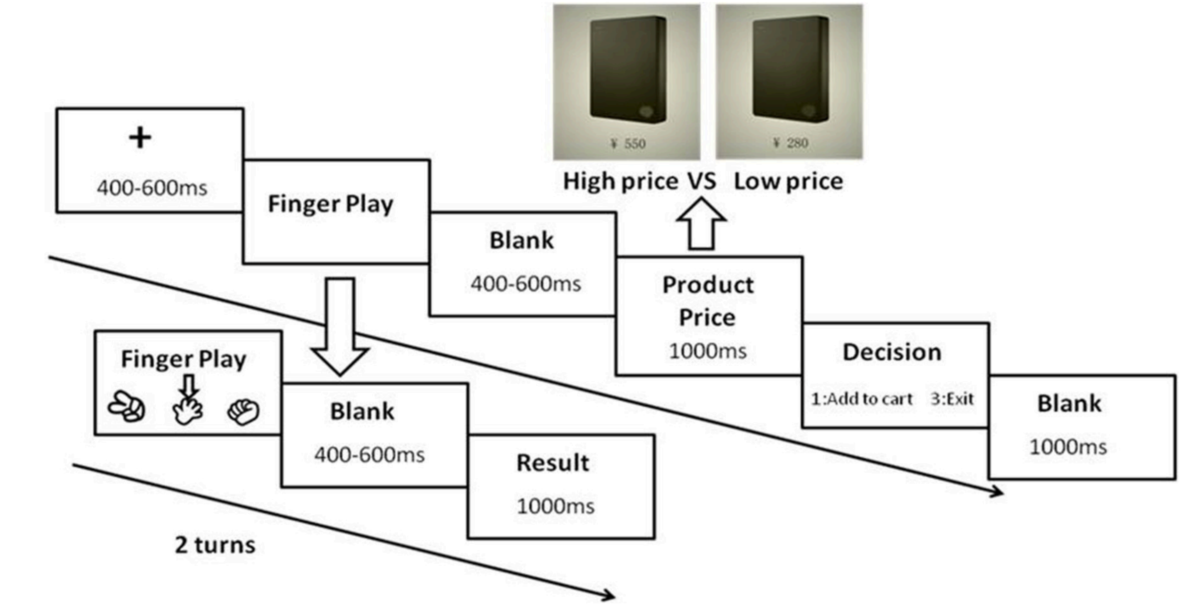

FIGURE 2 | A single trial of the ERP experiment.

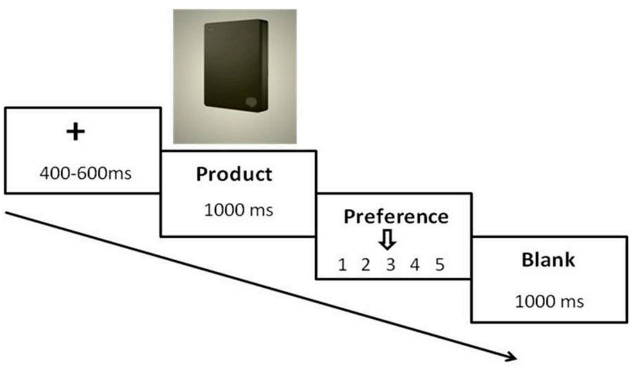

FIGURE 3 | A single trial of preference rating experiment.

Electrophysiological Recordings

Scalp voltages were recorded (band-pass 0.05–70 Hz, sampling rate 500 Hz) from a 64-channel electro-cap according to the 10/20 system and using a NeuroScan SynAmps 2 Amplifier (Scan 4.5, Neurosoft Labs, Inc. Virginia, USA). A cephalic (forehead) location was connected as the ground. EEGs were off-line re-referenced to the average of the left and the right mastoids. Horizontal Electrooculogram (EOG) was recorded at the left vs. right orbital rim while vertical EOG was recorded supra and infra-obitally at the left eye. The electrode impedance was maintained below 5 kΩ during the recording.

Data Analysis

For the behavioral data, descriptive statistics and T-test were used to analyze the ratio of adding to cart in the experiment. Further, a paired-samples T-test was adopted to analyze the preference degree ranking sores of hard-discs.

EEG data were pre-processed through the software NeuroScan 4.5 before the statistic analysis. EOG artifacts were corrected firstly, followed by digital filtering through a zero phase shift (low pass at 30 Hz, 24 dB/octave). The EEGs were segmented for 1,000 ms in each epoch, beginning 200 ms before and continuing until 800 ms after the onset of both the game results and products presentations. The entire epoch was then baseline-corrected by the 200 ms interval prior to the stimulus onset. Trials that contained amplifier clipping, bursts of electromyography activity, or peak-to-peak deflection exceeding ± 80 μV were excluded from the final average. Matlab R2015b was obtained to generate topographic maps for each condition.

The statistic method repeated measures ANOVA was adopted to do the statistics analysis of ERP results. In our study, the dependent variables of ANOVA with the FP game results onset were the amplitudes of P300 and LPP, respectively, and the independent variables were the two levels of finger play results [Single Win vs. Single Lose (SW vs. SL)/Continuous Win vs. Continuous Lose (CW vs. CL)/Single Win vs. Continuous Win (SW vs. CW)/Single Lose vs. Continuous Lose (SL vs. CL)] and the electrodes with nine levels (C1, Cz, C2, CP1, CPz, CP2, P1, Pz, P2). The dependent variables of ANOVA with hard-disc onset were the amplitudes of P2 and LPP, respectively, and the independent variables were hard-disc with price in four groups [high price hard-discs paired to continuous win (CWHP) vs. low price hard-discs paired to continuous win (CWLP) vs. high price hard-discs paired to continuous lose (CLHP) vs. low price hard-discs paired to continuous lose (CLLP)] and the electrodes with six levels (F3, Fz, F4, FC3, FCz, FC4) for P2 and nine levels (C1, Cz, C2, CP1, CPz, CP2, P1, Pz, P2) for LPP.

Based on the visual observation, the mean amplitudes from 290 to 400 ms of the central-parietal P300 and the mean amplitudes of LPP (from 500 to 800 ms) were mainly analyzed to examine the neural process when subjects knew the finger play results. Nine electrode sites from central parietal (C1, Cz, C2, CP1, CPz, CP2, P1, Pz, P2) were chosen for the analysis of P300 and LPP components. ANOVA factors were stimulus type (two levels: SW vs. SL or CW vs. CL or SW vs. CW or SL vs. CL) and electrodes (nine levels: C1, Cz, C2, CP1, CPz, CP2, P1, Pz, P2).

When a hard-disc picture was onset, the peak amplitude of early P2 component (in the range of 150–220 ms) was analyzed through six electrode sites (F3, Fz, F4, FC3, FCz, FC4) and the mean amplitude of late LPP component (from 500 to 800 ms) was analyzed through nine electrodes sites (C1, Cz, C2, CP1, CPz, CP2, P1, Pz, P2). ANOVA factors were price levels corresponding with FP results (four levels: CWHP vs. CWLP vs. CLHP vs. CLLP) and electrodes [six levels (F3, Fz, F4, FC3, FCz, FC4) for P2 and nine levels (C1, Cz, C2, CP1, CPz, CP2, P1, Pz, P2) for LPP]. The Greenhouse-Geisser correction was applied in all statistical analyses when necessary.

RESULTS

Behavioral Results

According to our research purposes, we only analyzed the adding to cart ratio of hard-discs corresponded to continuous win or continuous lose results and the preference ranking scores of pictures linked to these two conditions.

Results for "Adding to Cart" Task

Descriptive statistics was adopted to analyze the behavioral data. **Figure 4** showed the choice results subjects made in the experiment. The adding to cart proportion of CWHP was 55.1% ($SD = 0.36$), while the proportion of CLHP was 20.29% ($SD = 0.24$). Compared with CLLP ($M = 48.6\%$, $SD = 0.31$), the adding to cart proportion of CWLP was much higher ($M = 77.1\%$, $SD = 0.29$). The statistical results of paired-samples T-test also indicated that there were significant differences of adding to cart proportion among these four products groups ($t_{CWHP-CWLP}$ =2.119, $p = 0.046$; $t_{CLHP-CLLP} = 3.768$, $p = 0.001$; $t_{CWHP-CLHP} = 4.391$, $p < 0.01$; $t_{CWLP-CLLP} = 3.218$, $p = 0.004$).

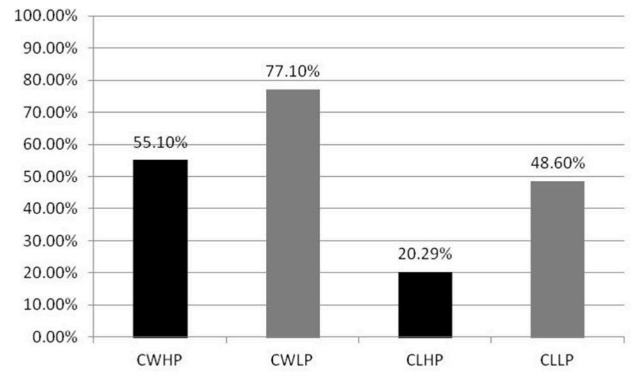

FIGURE 4 | The adding to cart proportion in four situations [CWHP (Continuous Win-High Price), CWLP (Continuous Win-Low Price), CLHP (Continuous Lose-High Price), and CLLP (Continuous Lose-Low Price)].

Results for Preference Rating Task

A paired-samples T-test was obtained to analyze the preference ranking scores of the hard-discs. Without the FP priming stimuli, subjects saw the products without price information directly and ranked nearly no differences in scores of preferences between products linked to CW results and CL results in the ERP experiment ($Mean_{Harddiscs-CW}$ =2.96, SD =0.369; $Mean_{Harddiscs-CL}$ =3.02, SD =0.357), and the T test result was not significant ($t = 0.835$, $p = 0.413$).

ERPS Results

FP Results Onset

We compared three situations' scalp waves which included SW vs. SL, CW vs. CL and SW/SL vs. CW/CL when FP result was onset. P300 and LPP components were observed in the situation (see **Figure 5** and **Table 1**).

P300

According to the statistical analysis, the main effect of FP results was significant ($F_{SW-SL-P300}$ =10.051, p=0.004; $F_{CW-CL-P300}$ =7.767, p =0.011; $F_{CW-SW-P300}$ =9.753, p=0.005; $F_{CL-SL-P300}$ =9.619, p=0.005). The amplitudes of SW and CW results were larger than SL and CL results. We also found larger P300 amplitudes of CW compared with SW, same as CL vs. SL ($Mean_{SW-P300} = 9.57\ \mu V$, $SD = 1.6$; $Mean_{SL-P300} = 8.24\ \mu V$, $SD = 1.44$; $Mean_{CW-P300} = 11.996\ \mu V$, $SD = 1.66$; $Mean_{CL-P300} = 10.45\ \mu V$, $SD = 1.55$).

LPP

The main effect of FP results was significant when we compared the CW vs. SW conditions as well as CL vs. SL conditions ($F_{CW-SW-LPP} = 5.091$, $p = 0.034$; $F_{CL-SL-LPP} = 6.584$, $p = 0.018$). Larger LPP amplitudes were elicited in CW and CL results compared with SW and SL results ($Mean_{SW-LPP} = 3.32\ \mu V$, $SD = 0.91$; $Mean_{SL-LPP} = 3.44\ \mu V$, $SD = 1.12$; $Mean_{CW-LPP} = 4.84\ \mu V$, $SD = 0.88$; $Mean_{CL-LPP} = 5.42\ \mu V$, $SD = 1.04$). However, the main effects of neither SW vs. SL nor CW vs. CL conditions were significant ($F_{SW-SL-LPP} = 0.05$, $p = 0.823$; $F_{CW-CL-LPP} = 1.42$, $p = 0.246$).

Hard-Discs With High or Low Prices Onset

According to the visual observation, the late positive potentials component (LPP) was mainly analyzed of the neural process. In addition, the early P2 was also observed when we compared the CWHP and CLHP conditions (see **Table 2**).

P2

The main effect of Continuous Win compared with Continuous Lose in High Price condition was significant ($F_{CWHP-CLHP-P2} = 4.398$, $p = 0.048$) and larger peak amplitude was elicited in CWHP condition ($Mean_{CWHP-P2} = 1.508\ \mu V$, $SD = 0.665$; $Mean_{CLHP-P2} = 0.561\ \mu V$, $SD = 0.678$). The latencies of these two conditions had

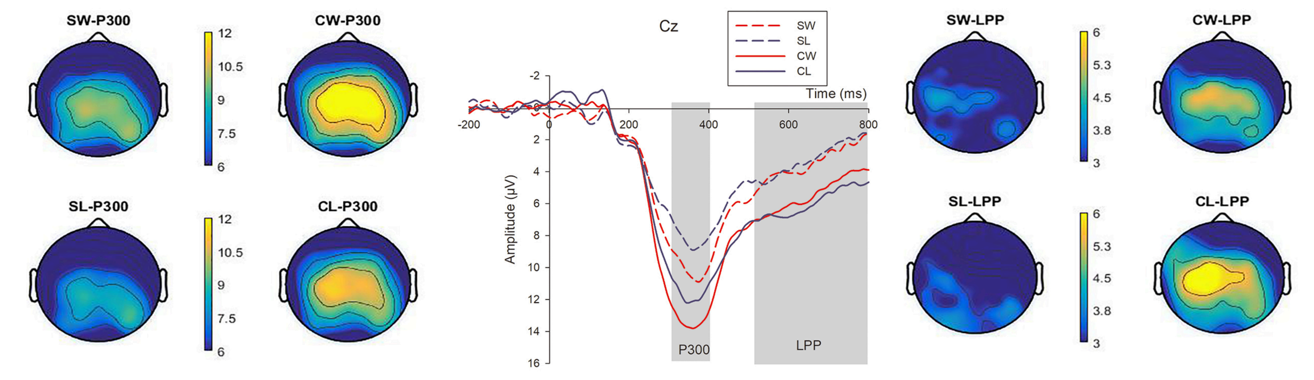

FIGURE 5 | The ERP grand-average waveforms at Cz and topographical maps of P300 and LPP in four game results conditions ["SW" (Single Win), "SL" (Single Lose), "CW" (Continuous Win), and "CL" (Continuous Lose)]. The time window for P300 was 290–400 ms, while 500–800 ms for LPP. The bar of the topographical map ranges from 6–12 μV for P300 to 3–6 μV for LPP.

no significant difference ($F_{CWHP-CLHP-P2Latency} = 0.552$, $p = 0.465$; $Mean_{CWHP-P2Latency} = 186.87$ ms, $SD = 3.852$; $Mean_{CLHP-P2Latency} = 189.58$ms, $SD = 4.037$) (see **Figure 6**). However, we did not find significant differences across other conditions ($F_{CWHP-CWLP-P2} = 1.186$, $p = 0.288$; $F_{CLHP-CLLP-P2} = 0.947$, $p = 0.341$; $F_{CWLP-CLLP-P2} = 0.042$, $p = 0.84$; $Mean_{CWLP-P2} = 0.978\ \mu V$, $SD = 0.645$; $Mean_{CLLP-P2} = 1.064\ \mu V$, $SD = 0.731$).

LPP

The main effects of CWHP vs. CLHP was significant ($F_{CWHP-CLHP-LPP} = 6.274$, $p = 0.02$). Larger mean amplitudes from 500 to 800 ms of late positive potentials were observed of CWHP compared with CLHP ($Mean_{CWHP-LPP} = 2.364\ \mu V$, $SD = 0.972$; $Mean_{CLHP-LPP} = 1.138\ \mu V$, $SD = 0.879$). We did not find significant differences of LPP effects among CWLP vs. CLLP, CLHP vs. CLLP and CWHP vs. CWLP conditions ($F_{CWLP-CLLP-LPP} = 0.16$, $p = 0.693$; $F_{CLHP-CLLP-LPP} = 0.136$, $p = 0.716$; $F_{CWHP-CWLP-LPP} = 0.022$, $p = 0.884$; $Mean_{CWLP-LPP} = 1.764\ \mu V$, $SD = 0.812$; $Mean_{CLLP-LPP} = 1.558\ \mu V$, $SD = 0.784$). However, we examined the latency of peak amplitudes of LPP during the 500–800 ms time duration and found significant differences between CWLP and CLLP conditions ($F_{CWLP-CLLP-LPPLatency} = 7.925$, $p = 0.01$; $Mean_{CWLP-LPPLatency} = 609.45$ ms, $SD = 13.482$; $Mean_{CLLP-LPPLatency} = 662.37$ ms, $SD = 12.636$; see **Figure 7**).

DISCUSSION

There were two main purposes of this study. One was to examine whether the two-player "Finger Play" game without monetary gains or losses could be an emotional priming paradigm using in an event-related potentials experiment. The other was to investigate the neural process of emotions influencing subjects' price perceptions and their buying behavior. According to our experiment results, these two objectives were both achieved through the behavioral data and ERPs measures.

A growing consensus in recent years witnessed that there were tightly intertwined of affective and cognitive processes (Olofsson et al., 2008; Winkielman and Gogolushko, 2018). Both psychological function and neural substrates offered evidences to understand the mechanisms of this connection (LeDoux, 2012; Pessoa, 2013, 2015). Subsequent studies discovered the influence of visually suppressed affective pictures including face expressions or emotional words on a variety of reactions, behaviors, judgments and decisions. Emotion-related researches normally adopted affective pictures or emotional words as the priming stimuli (Begleiter et al., 1967; Sweeny et al., 2009; Axelrod et al., 2015; Diéguez-Risco et al., 2015; Zhang et al., 2015; Chanes et al., 2018). Existing research findings expounded that winning or losing might induce positive or negative emotions in sports games or gambling (Lole et al., 2013; Doron and Gaudreau, 2014; Tomer et al., 2014; Sacré et al., 2016; Kamei et al., 2018), yet few studies adopted it as an emotional priming and integrated it to investigate with other topics especially business or marketing issues. To our best knowledge, we firstly employed a two-player FP game as an emotional priming paradigm and integrated it into a price perception investigation. The reason we chose FP game was because it was easily understood and nearly everyone knew the playing rules. In addition, monetary gains or losses were out of consideration as it might cause other complexity mental issues which were not our research emphasis. More important, we recruited two subjects to do the ERP experiment in different rooms and recorded the data at the same time. Those two participants signed on the informed consents and read the experimental instructions together before the formal experiment. The reason for doing that was to create and strengthen the sense of authenticity and presence upon subjects according to hyper-scanning techniques using in neuroscience (Montague et al., 2002; Ma et al., 2011).

According to our ERP measures, larger amplitudes of parietal P300 were elicited of winning (SW and CW) compared with losing (SL and CL) situation (see **Figure 5**). As mentioned by Yeung and Sanfey (2004), P300 was sensitive to the reward value of alternative, non-selected stimuli (Yeung and Sanfey, 2004).

TABLE 1 | ANOVA Results of FP results onset.

Source		Value	*F*	Hypothesis df	Error df	Sig.
P300 (290–400 ms)						
SW vs.SL	Pillai's Trace	0.314	10.051[a]	1.000	22.000	0.004
	Wilks' Lambda	0.686	10.051[a]	1.000	22.000	0.004
	Hotelling's Trace	0.457	10.051[a]	1.000	22.000	0.004
	Roy's Largest Root	0.457	10.051[a]	1.000	22.000	0.004
CW vs. CL	Pillai's Trace	0.261	7.767[a]	1.000	22.000	0.011
	Wilks' Lambda	0.739	7.767[a]	1.000	22.000	0.011
	Hotelling's Trace	0.353	7.767[a]	1.000	22.000	0.011
	Roy's Largest Root	0.353	7.767[a]	1.000	22.000	0.011
CW vs. SW	Pillai's Trace	0.307	9.753[a]	1.000	22.000	0.005
	Wilks' Lambda	0.693	9.753[a]	1.000	22.000	0.005
	Hotelling's Trace	0.443	9.753[a]	1.000	22.000	0.005
	Roy's Largest Root	0.443	9.753[a]	1.000	22.000	0.005
CL vs. SL	Pillai's Trace	0.304	9.619[a]	1.000	22.000	0.005
	Wilks' Lambda	0.696	9.619[a]	1.000	22.000	0.005
	Hotelling's Trace	0.437	9.619[a]	1.000	22.000	0.005
	Roy's Largest Root	0.437	9.619[a]	1.000	22.000	0.005
LPP (500–800 ms)						
CW vs. SW	Pillai's Trace	0.188	5.091[a]	1.000	22.000	0.034
	Wilks' Lambda	0.812	5.091[a]	1.000	22.000	0.034
	Hotelling's Trace	0.231	5.091[a]	1.000	22.000	0.034
	Roy's Largest Root	0.231	5.091[a]	1.000	22.000	0.034
CL vs. SL	Pillai's Trace	0.230	6.584[a]	1.000	22.000	0.018
	Wilks' Lambda	0.770	6.584[a]	1.000	22.000	0.018
	Hotelling's Trace	0.299	6.584[a]	1.000	22.000	0.018
	Roy's Largest Root	0.299	6.584[a]	1.000	22.000	0.018

[a]*Means the exact statistic.*

P300 was also thought to reflect the magnitude of rewards or favorable outcomes (Yeung and Sanfey, 2004; Sato et al., 2005; Luo and Qu, 2013). A more favorable split generated a larger P300 than an unfavorable one (Wu et al., 2011, 2012). In addition, larger P300 amplitudes revealed positive outcomes than negative ones (Hajcak et al., 2004; Yeung et al., 2005; Peterburs et al., 2013). There were no monetary gains or losses in our research design, however, the simple results of win and lose activated subjects' reward area of brain and brought emotion changes as well. It might reveal that subjects exactly "loved to win and hated to lose" through ERPs evidences. Furthermore, larger amplitudes of late positive potentials (LPP) were evoked in CW and CL results compared to SW and SL situations (see **Figure 5**). The latter portion of ERP waveform LPP indicated elevated positivity to high-arousing stimulation according to Cuthbert et al. (2000). Cuthbert et al. (2000) in our study, when subjects had continuous win or continuous lose experiences, higher arousing emotion intensity had been elicited compared with single win or single lose experiences. Gajewski et al. (2016) used facial expression as stimuli in their study to analyze the neural correlates of a simulated purchase decision task. However, no significant effects were found by facial expression upon participants' neural process. The explanation might be those facial pictures were irrelevant with the shopping task in their experiment. In our study, we simulated a virtual online interactive game (FP) developed by the shopping website and gave a good reason (would receive coupons for next shopping) to subjects to accept playing the game before browsing products. In this context, FP priming well combined with the adding to cart task. As a result, the emotional reflection of FP results made a significant influence upon subjects' perception of products price and their behavior.

According to the preference rating scores of the selected hard-discs, it was revealed that subjects' attitudes regarding the products without price information were discrete. They made a decision whether adding the hard-disc to cart or not only depending on the difference price information or their intuition. Knutson et al. (2007) suggested that consumers mostly avoided excessive prices products in addition to those deeply preferred ones (Knutson et al., 2007). In our case, subjects were assumed to choose cheaper hard-discs as all the products properties were nearly the same. Interestingly, subjects' choices were impacted to a great extent by different arousal emotions when continuous winning or continuous losing in the FP game induced. The adding to cart proportion of CWHP ($M = 55.1\%$, $SD = 0.36$) was higher than CLHP ($M = 20.29\%$, $SD = 0.24$). Meanwhile, the adding to cart proportion of CWLP ($M = 77.1\%$, $SD = 0.29$) was much higher either compared with CLLP ($M = 48.6\%$, $SD = 0.31$). It was easily to understand that

TABLE 2 | ANOVA results of hard-discs with high or low price onset.

Source		Value	*F*	Hypothesis df	Error df	Sig.
P2 (150–220 ms)						
CWHP–CLHP	Pillai's Trace	0.167	4.398[a]	1.000	22.000	0.048
	Wilks' Lambda	0.833	4.398[a]	1.000	22.000	0.048
	Hotelling's Trace	0.200	4.398[a]	1.000	22.000	0.048
	Roy's Largest Root	0.200	4.398[a]	1.000	22.000	0.048
LPP (500–800 ms)						
CWHP-CLHP	Pillai's Trace	0.222	6.274[a]	1.000	22.000	0.020
	Wilks' Lambda	0.778	6.274[a]	1.000	22.000	0.020
	Hotelling's Trace	0.285	6.274[a]	1.000	22.000	0.020
	Roy's Largest Root	0.285	6.274[a]	1.000	22.000	0.020
LPP Latency						
CWLP–CLLP	Pillai's Trace	0.265	7.925[a]	1.000	22.000	0.010
	Wilks' Lambda	0.735	7.925[a]	1.000	22.000	0.010
	Hotelling's Trace	0.360	7.925[a]	1.000	22.000	0.010
	Roy's Largest Root	0.360	7.925[a]	1.000	22.000	0.010

[a] *Means the exact statistic.*

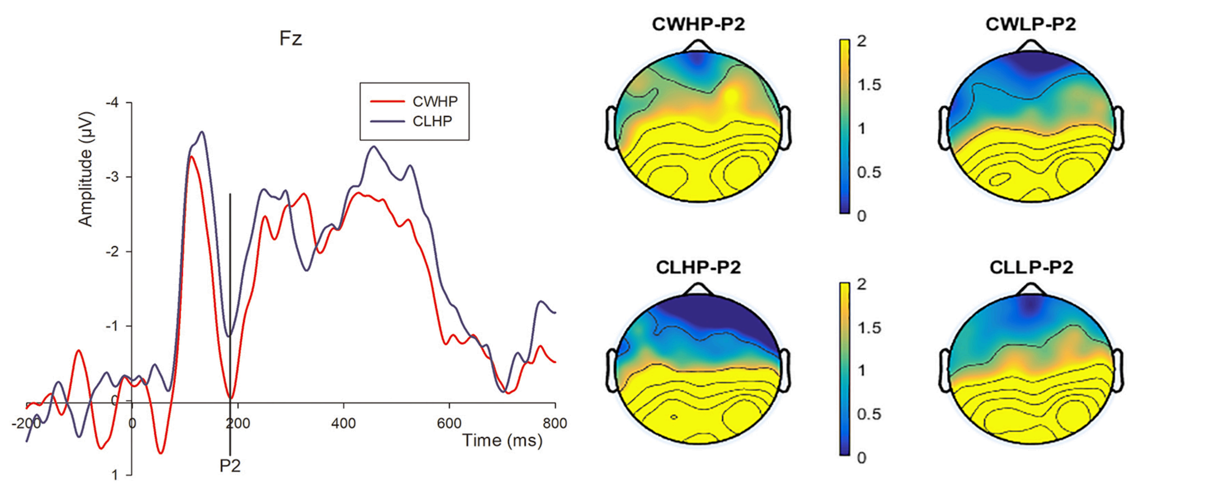

FIGURE 6 | The comparison of the peak-average waveforms from 150 to 220 ms at Fz and topographical maps of P2 in CWHP and CLHP conditions. The bar of the topographical map ranges from 0 to 2 μV.

higher adding ratio of low price hard-discs than high price ones. When we compared the adding proportion in same emotion situations (CW or CL), low price hard-discs were added to cart more than high price ones. However, the adding ratios of either high price or low price hard-discs were higher in CW situation than in CL situation (see **Figure 4**). It might be clearer to explain this phenomenon through the event-related potential measures. According to the visual observation and statistical analysis, two main ERP components—P2 and LPP were found when we compared CWHP and CLHP conditions. Standard ERP recording methods indicated that P2 component was sensitive to the onset of pleasant-going arousal-related amplitude modulation persisting until stimulus offset (Carretié et al., 2001a,b; Amrhein et al., 2004; Olofsson and Polich, 2007; Olofsson et al., 2008). Kamei et al. (2018) also observed that the auditory P2 and the occurrence of pleasant emotions were higher in the winning streak (WS) condition than in the losing streak (LS) condition (Kamei et al., 2018). Similar to Kamei et al. (2018), a larger P2 peak-amplitude from 150 to 220 ms was observed in CWHP compared with CLHP condition, might because CW elicited more positive emotions than CL and this emotion state was lasting then continuously influenced subjects' price perception resulting higher adding ratio of CWHP than CLHP (see **Figures 4**, **6**). In addition, larger LPP amplitudes had been observed in CWHP compared to CLHP either (see **Figure 7**). Hajcak et al. (2010) concluded that emotional influences on the LPP related to the emotional intensity of stimuli (Hajcak et al., 2010). In our study, high price hard-discs corresponded with CW condition elicited larger LPP amplitudes than CL condition. CW aroused a more intense emotion than CL and this highly

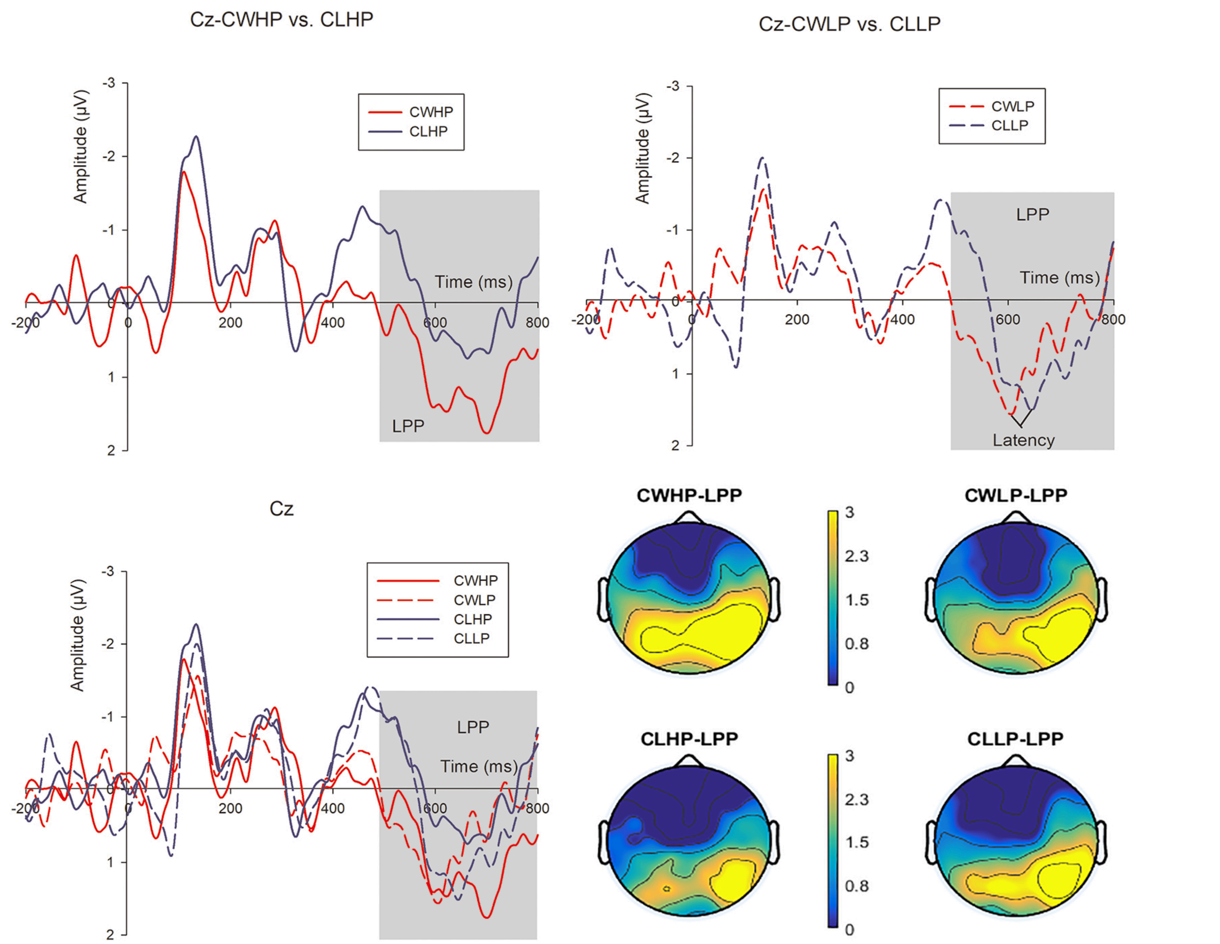

FIGURE 7 | The LPP grand-average waveforms from 500 to 800 ms at Cz and the topographical maps in the four conditions: CWHP, CWLP, CLHP, and CLLP. The bar of the topographical map ranges from 0 to 3 μV.

arousal emotion lasted when products with price onset then changed subjects' price perception and finally caused a higher adding ratio of CWHP. The adding to cart proportion of CWLP was higher than CLLP as well on the basis of the behavioral data. In ERP measures, we found a significant difference in latencies of peak amplitudes during the time window 500–800 ms between CWLP and CLLP. The peak amplitudes of late positive potentials occurred earlier in CWLP ($Mean_{CWLP-LPPLatency}$ = 609.45 ms, SD = 13.482) than CLLP ($Mean_{CLLP-LPPLatency}$ = 662.37 ms, SD = 12.636) condition (see **Figure 7**). That might explain why higher adding ration of CWLP compared with CLLP.

However, we did not find effective ERP components when we examined other conditions (CWHP vs. CWLP, CLHP vs. CLHP). This further illustrated that in the same emotion condition, subjects made decisions based on their common sense and had more dependence on their past experiences.

The findings of this study indicated that emotions indeed played an important role in consumers' price perception and influenced their buying behavior. Additionally, the new experimental paradigm we creatively used could be applied in other marketing research issues. Win or lose feelings might impact not only customers' price perception, but also their other purchasing processes. However, the observation of brain-behavior relationship of our study was under well-controlled laboratory conditions and the ecological validity of the research might be limited. The customers' actual buying behavior might be dissimilar from our experimental settings. In the real marketing environment, the decision process of purchase might be more complicated and the information searching time might be much longer. There were some areas needed to improve in our future research. Firstly, the design of experiments needed to better reflect participants' real buying processes. Secondly, studies on how continuous win effect influenced consumer's buying behavior needed to be applied in other marketing issues, such as brand preference, product design, advertising etc. Moreover, mobile EEG equipment could be adopted to record customers' brain activities outside the laboratory but in more natural situations (Bleichner et al., 2015).

CONCLUSION

To sum up, this study creatively integrated a competitive game without monetary gains or losses as an emotional priming paradigm into the investigation of how emotions influencing subjects' price perception. Both behavioral and ERP results indicated that subjects' price perception was deeply impacted by emotions. Emotions induced by winning include Single Win and Continuous Win were more positive than those evoked by losing include Single Lose and Continuous Lose situations. Continuous Win and Continuous Lose aroused more intensity emotions compared to Single Win and Single Lose. These emotion states lasted when hard-discs with price presented to subjects and evoked P2 and LPP components in CWHP and CLHP conditions as well as latency differences between CWLP and CLLP conditions. Thus, subjects added more hard-discs to cart when they experienced continuous win results compared to continuous lose situation. It was verified that emotion played an important role in consumer behavior and marketing from a new angle. Moreover, we firstly proposed this phenomenon as a new concept—"Continuous Win Effect" and planned to do more relative researches on this topic. Nevertheless, there still were some limitations in our research. First of all, the experimental setting might be very different from consumers' actual buying behavior. In the real marketing place, the decision process of purchase might be more complicated and the information searching time might be much longer. Secondly, we only tested the results of winning and losing without considering the situation of draw and others. Third, we only examined price perception of a well-known electronic product—mobile hard-disc without considering other products such as luxury goods, furniture, foods and beverages etc. The question might be whether emotions could impact price perceptions and consumers' behavior on these products as well or not. These deficiencies would be improved in future researches.

ETHICS STATEMENT

As corresponding author, Qingguo MA confirmed that all experiments were performed in accordance with relevant guidelines and regulations. All experiments were approved by the Neuromanagement Laboratory Ethics Committee at Zhejiang University and reviewed by the ethics committee. The research design respects the personality of the subjects and will not cause psychological and physical damage to the subjects. The experiments are performed in accordance with APA Ethics Code and the principle of <International Ethical Guidelines for Biomedical Research Involving Human Subjects> by CIOMS. Further, written informed consent was obtained from all participants prior to the ERP experiments.

AUTHOR CONTRIBUTIONS

QM designed the experiments. LZ and MW prepared the experiments and collected behavioral and ERP data. LZ processed and analyzed data. QM and LZ wrote the main manuscript text and prepared all the figures. All authors reviewed the manuscript.

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Corrigendum: "You Win, You Buy"—How Continuous Win Effect Influence Consumers' Price Perception: An ERP Study

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How Is the Neural Response to the Design of Experience Goods Related to Personalized Preference? An Implicit View

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Understanding the process by which consumers evaluate the designs of experience goods is critical for firms designing and delivering experience products. As the implicit process involved in this evaluation, and given the possible social desirability bias inherent to traditional methods of product design evaluation in certain conditions, neuroscientific methods are preferred to gain insight into the neural basis of consumers' evaluation of experience good designs. We here used event-related potentials (ERPs) and a revised go/no-go paradigm to investigate consumers' neural responses to experience good designs. Personalized product designs and neutral landscape pictures were randomly presented to 20 student participants; they were asked to view these product designs without making any decisions. The paired *t*-test and repeated-measures analysis of correlation showed that the P200 and late positive potential (LPP) elicited by the most-preferred experience good designs were significantly higher than that elicited by least-preferred designs, and the two ERP components were positively correlated with the personalized rating scores. Thus, P200 and LPP might be the early and late indices of consumers' evaluation of experience good designs, respectively, and may facilitate an understanding of the temporal course of this evaluation. Furthermore, these two ERP components can be used to identify consumers' preferences toward experience good designs. In addition, given the use of personalized experimental stimuli, these findings may help to explain why customized products are preferred by consumers.

Keywords: event-related potentials, experience goods, late positive potential, P200, personalized product designs

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INTRODUCTION

Design is an inherent component of all products, and has a lasting effect on consumers' loyalty to brands and their purchasing decisions (Reimann et al., 2010; Homburg et al., 2015). Experience goods, such as clothes, wines, and cosmetics, are products whose utility cannot be ascertained before purchase, because of the lack of full information (Nelson, 1970, 1974). Product design is especially important for such goods, because product design is an important source of utility of experience goods. For example, besides the functional dimension, the esthetic and symbolic dimension of T-shirts are also important parts of T-shirt designs (Homburg et al., 2015), and they are also the key factors influencing consumers' experience evaluation of T-shirts. More important, product design is the main source of uncertainty in consumers' evaluation of experience goods. Compared to search attributes of experience products, such as material and price, consumers' evaluation of experience attributes of these goods, such as product designs, is more subjective (Huang et al., 2009), and their needs for experience attributes are more personalized (Bloch et al., 2003). Therefore, it is difficult for enterprises to understand consumers' demand for experiential good designs effectively, and for consumers to use the information provided by firms to judge the fit between their needs and experience good designs, which will increase the uncertainty of consumers' evaluation of experiential products. In practice, some T-shirt, mobile phone case, and cake firms have even given up on understanding of the consumers' needs for experience product designs, and have outsourced the product design task to consumers through personalized customization (Schreier, 2006). The basic premise of personalized customization is to let consumers choose the design elements that they like, while the firms complete the production and distribution. Therefore, exploring consumers' process of evaluating experience product designs can shed light on the consumer needs for experience products and provide important information to enterprises for designing and delivering experience goods.

The evaluation of product designs is an esthetic evaluation process, which has been found to be associated with consumers' cognitive and emotional responses (Silvia and Warburton, 2006), and is influenced by the existing knowledge and experience of consumers. This makes the consumers' evaluation of product designs more subjective and personal. Therefore, relatively objective measures are needed to capture the process and characteristics of product design evaluation (Luo et al., 2008; Pearce et al., 2016). Additionally, the implicit information processing involved in this esthetic evaluation process of product designs makes the traditional questionnaire method less effective in this study (Wang and Tseng, 2015). For example, questionnaires can be used to elicit consumers' explicit preference for experience product designs, but it cannot explain the implicit reasons for this preference. In addition, for products that satisfy consumers' social communication and status-seeking need (Heine and Phan, 2011), such as luxury goods, and for participants who participate in product preference evaluation in order to obtain monetary rewards (Davidson et al., 2002), directly eliciting consumers' response to product designs using questionnaire may cause social desirability bias.

The event-related potential (ERP) technique can directly measure individuals' perceptual and cognitive processes in response to stimuli with high temporal resolution (Luck et al., 2000), and can help to record the activities that involve social-desirability biases or are otherwise difficult to report (Cerf et al., 2015). It can also help to discover physiological factors that influence individual behavior and preferences and explore the "common scale" that allows comparison of heterogeneous and individualized behavior (Levy and Glimcher, 2012; Camerer and Yoon, 2015). Studies have explored the neural processes and brain regions involved in the evaluation of esthetic objectives by means of EPRs, for example, arts (Augustin et al., 2011) and faces (Chatterjee et al., 2009). For product designs, in addition to the esthetic aspect, such as arts and music, the symbolic aspect is also important and is significantly related to consumer behavior (Homburg et al., 2015).

Previous studies have also adopted the ERP technology to study consumers' preference using product images and have indicated that some ERP components can effectively predict consumer preferences and choices (Junghöfer et al., 2010; Pozharliev et al., 2015; Telpaz et al., 2015). Nevertheless, these studies did not considered differences between different types of products, except for the study by Pozharliev et al. (2015), which explicitly focused on luxury goods. In fact, consumers consider different factors when purchasing different types of products. For example, for search goods, the objective attributes (e.g., price and functions) are influential in the decision-making process (Huang et al., 2009). The EEG signals collected when consumers view the product images (subjective attributes) of search goods cannot capture the key information of consumers' decision-making process, and the predictive relationship of EEG signals and product preferences is also not accurate. For experience goods, the subjective attributes (e.g., product designs) are important (Hoch and Ha, 1986). EEG signals collected when consumers view the product images can capture the process of consumers' evaluation of product (designs) more accurately. In addition, in these studies, all the subjects were assigned to view the same product design images, and the subjective and penalized demand of consumers for product designs was not appropriately considered. For experience goods, for which subjective attributes are important (Hoch and Ha, 1986), EEG signals collected when viewing the same product design pictures as previous studies may not capture the individualized differences in consumers' evaluation of product designs. Thus, by using personalized experimental stimuli and ERP technology, this study focused on the process of evaluation of experience product designs.

Product design evaluation is correlated with esthetic evaluation (Bloch, 1995; Silvia and Warburton, 2006). Previous studies have posited that esthetic evaluation consists of two distinct stages: early impression formation and a subsequent evaluative categorization stage (Celaconde et al., 2013). During the early impression formation phase, individuals devote more attentional resources to exploring stimuli. The subconscious processes and visual properties of the stimuli are involved in this stage (Celaconde et al., 2004). P200 is a positive-going waveform with a peak latency at about 200 ms after the onset of stimuli, and is related to early automatic and selective attention (Olofsson et al., 2008). P200 can be elicited by affective stimuli, reflecting the initial sensory encoding of emotionally significant stimuli, and the onset of a persistent positive shift of the ERP waveform (Olofsson et al., 2008). As individuals pay more visual attention to product designs that they find attractive (Coates, 2003), we speculated that a greater positive-going amplitude would be observed in P200 for the most-preferred product designs of experience goods than for the least-preferred designs.

In the evaluative categorization stage, more conscious and cognitive appraisals are triggered, which result in a more enduring esthetic judgment and emotional response (Kumar and Garg, 2010; Celaconde et al., 2013). The late positive potential (LPP) is a long-lasting ERP component peaking at around 500–700 ms after the onset of stimuli. An enhanced LPP amplitude represents a reliable, replicable, and time-specific emotional response to stimuli (Hajcak et al., 2006). The LPP amplitude is positively correlated with arousal level, which implies that pictures causing high emotional arousal (pleasant or unpleasant, rather than neutral) elicit augmented LPP (Schupp et al., 2000). The LPP also indicates the sustained enhanced attention allocation and motivational significance of emotional visual stimuli during affective perceptual processing (Bradley et al., 2003). As most-preferred product designs of experience goods will elicit more emotional arousal than less-preferred designs, and individuals reliably allocate more attention to the former (Coates, 2003), we speculated that greater positive-going amplitude of LPP would be observed for the most-preferred experience goods designs than that for the least-preferred designs. Moreover, according to neuropsychological models of attention, P200 and LPP are correlated and jointly reflect different attentional processes for the same visual stimulus (Pozharliev et al., 2015). Therefore, we speculated that the two ERP components would both be evoked during the product design evaluation process of experience goods.

In this study, we analyzed the neural activities related to the design evaluation of experience goods. We speculated that more positive-going ERP amplitude would be observed for the two ERP components, P200 and LPP, for the most-preferred experience good designs than that for the least-preferred designs. To investigate the personal and subjective nature of product design evaluation, we used personalized product designs rather than the same stimulus for all the participants in the experiment, since personalized stimuli may reflect individuals' preferences for product designs more accurately (Pearce et al., 2016).

MATERIALS AND METHODS

Study Participants

The participants were 20 students recruited from Ningbo University, aged 18–26 years of age (mean age = 24 years, SD = 2.247; 53% women). All the participants reported normal or corrected-to-normal vision and had no history of neurological or psychiatric illness. The participants were paid ¥40 as compensation for participation in the study. Four of the participants were removed from the study due to excessive ERP artifacts. This study was approved by the local institutional ethics committee of the Academy of Neuroeconomics and Neuromanagement at Ningbo University. All participants provided written informed consent before the experiment started.

Study Materials

Considering the familiarities of the participants and the needs for personalized experimental stimuli, we selected the T-shirts as experimental stimuli. Using the three-dimensional scale reported by Weathers et al. (2007), we measured the perceived product type of T-shirts of 30 students (recruited from the same university as those for the main experiment), the average score of the three dimensions was 4.910 (1 = pure search goods, 7 = pure experience goods), which indicate that T-shirts were more likely to be perceived as experience rather than search goods.

The current common practice of implementing "personalized T-shirt design" is as follows: first, firms post design elements on their website; then, consumers choose and combine design elements by themselves; finally, T-shirts are manufactured and derived according to the consumers' preference. As this is time-consuming and is not easy to implement in the laboratory, we asked the research assistants to select the images of the T-shirt designs of five major T-shirt brands from their official websites on Tmall.com (choosing the new and personalized designs). We also used the Baidu search engine to select 40 neutral landscape images for implicit tasks. All the pictures were processed to have a white background, a resolution of 360 × 270 pixels, and were in pdf format. The size of these pictures was 360 mm × 360 mm. There were no explicit brand names, logo, or other explicit signals on the product design pictures.

Experimental Procedures and EEG Recording

The experiment was divided into two stages (**Figure 1**). In the first stage, participants were told that these T-shirt designs were randomly combined using the design elements of T-shirt customization companies on Tmall.com, and they were asked to indicate their preference for these T-shirt design pictures. Their preference was measured using a 0–100 horizontal preference scale (100 = completely prefer the design pictures). In order to increase the accuracy of subjective measurement, participants were told that "there are no right or wrong answers in the evaluation of the T-shirt designs; please give your true preference. Your evaluation will only be used for this study, and we will keep your answers strictly confidential." We did not record the name and other personal information of these participants. The survey was conducted in an independent behavioral laboratory and there was no interference throughout the process.

After scoring, participants were invited to attend the second stage of the experiment, which was conducted in a dimly lit and electrically shielded EEG laboratory. The design of this experiment followed a revised go/no-go paradigm, in which the participants were instructed to "go" (press a key) when a landscape picture was presented, and to "no-go" (refrain from pressing a key) when a T-shirt picture was presented. The ERP experiment consisted of three blocks, and each block contained 40 trials. For each participant, there were two groups of 40 personalized T-shirt pictures (most-preferred and least-preferred product designs), and one group of 40 landscape pictures. The two groups of T-shirt pictures were classified based on the self-rating scores allotted to these pictures in the first stage. The 40

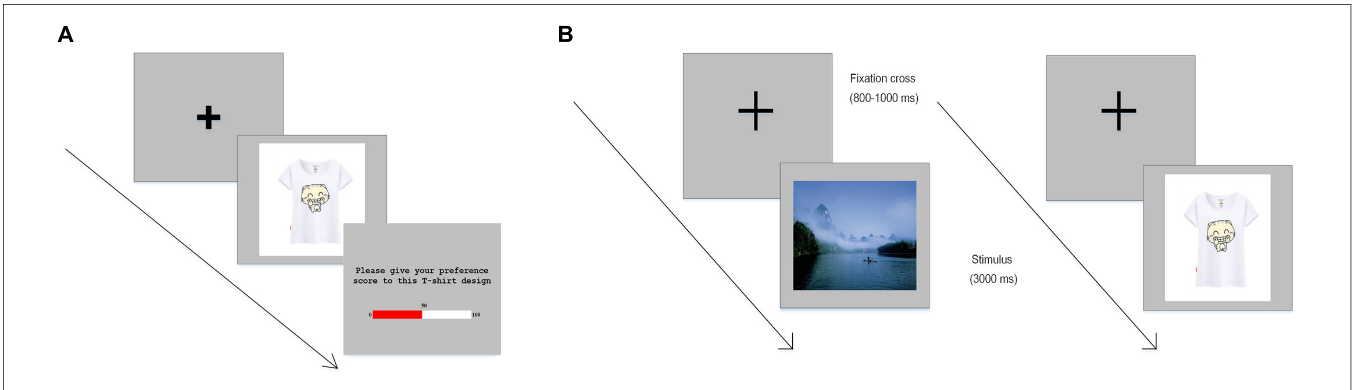

FIGURE 1 | Example trials of the experiment. **(A)** T-shirt preference rating task. During each trial, after a fixation cross appeared, participants were presented with a picture of a T-shirt, and then they were instructed to give their preference scores for the T-shirt. **(B)** Landscape picture and product design presentation in the ERP task. In each trial, after a fixation cross appeared, landscape pictures and product designs were presented randomly. Participants were instructed to view these pictures without making any decisions regarding the product designs and to press a key for landscape pictures.

landscape pictures were discarded at the data analysis stage. All the pictures were presented in a randomized order. Participants were instructed to watch these pictures without making any overt responses, and to minimize head and body movements during this stage.

The pictures were presented on a 19-in monitor (1280 × 1024 pixels, 60 Hz), which was connected to a 2 GHz Pentium computer. E-prime 2.0 (Psychology Software tools, Pittsburgh, PA, United States) was used for stimulus presentation and data collection. The pictures were positioned at the center of the screen and viewed from a distance of 100 cm, at a visual angle of 6.27–6.271°. The background of the screen was gray (RGB: 128, 128, 128).

Event-related potential data were recorded using 64 Ag/AgCl electrodes mounted on an elastic cap with a Neuroscan Synamp2 Amplifier (Scan 4.3.1, Neurosoft Labs, Inc.). A forehead location was used for grounding, and the reference was the left mastoid. Using left and right mastoid references, data were transferred to the average offline. Vertical electrooculograms were recorded using a pair of electrodes placed above and below the right eye, while horizontal electrooculograms were recorded using another pair of electrodes placed on the right side of the right eye and left side of the left eye. Both vertical and horizontal pairs of electrodes were placed 10 mm from the eyes. Electrooculogram artifacts were corrected offline. The experiment started with the impedances of the electrodes less than 5 kΩ.

Epochs were made beginning 200 ms before stimulus onset and continuing for 800 ms after the onset. The EEG was aligned to a 200-ms baseline, and error-of-commission artifacts were corrected using the method proposed by (Semlitsch et al., 1986). Trials with bursts of electromyography activity, peak-to-peak deflection exceeding ± 100 μV, and amplifier clipping were excluded. The averaged ERPs were digitally filtered using a low-pass filter at 30 Hz (24 dB/octave). The EEG recordings for every participant were averaged separately over each recording site for each of the most- and least-preferred product design conditions. The data were further analyzed for the two experimental conditions.

Statistical Analysis

Previous studies have indicated that the modulation of the P200 amplitude to emotional visual stimuli is most pronounced in the posterior scalp areas (Schupp et al., 2004; Pozharliev et al., 2015), and that the LPP is most pronounced in the superior–posterior scalp areas (Sabatinelli et al., 2006; Pozharliev et al., 2015). These two components, elicited by the emotional visual stimuli, are usually reported in both the left and right hemispheres (Dolcos and Cabeza, 2002). Based on these findings, for P200, we analyzed signals from the following nines electrodes: C1, CZ, C2, CP1, CPZ, CP2, P1, PZ, and P2. As the nine electrode sites in the posterior area had a similar pattern of results, the data from the region were pooled to obtain a representative value. For the LPP, we focused on the following six electrodes: C1, CZ, C2, CP1, CPZ, and CP2, the data from all the six electrode sites in the central and parietal scalp areas were also pooled for the same reason as for P200.

Based on previous studies and visual inspection of grand averages of waveforms (Pozharliev et al., 2015), the time windows chosen for P200 and the LPP were 160–210 and 500–700 ms, respectively. For each participant, we examined the P200 and LPP amplitude in the most- and least-preferred conditions and matched these amplitudes with the average preference rating scores for the personalized product designs under both conditions. We examined whether there were significant differences in the ERP amplitude for different preference conditions, and how the ERP components induced by product designs were correlated to the corresponding personalized preference rating scores. As product designs that were presented to the participants were nested within the subjects, the pairwise t-test and repeated measures analysis of correlation were used.

RESULTS

The average scores for T-shirt designs of the five brands were 52.71, 51.66, 52.24, 53.23, and 50.47, and repeated measures ANOVA revealed that there was no significant difference between

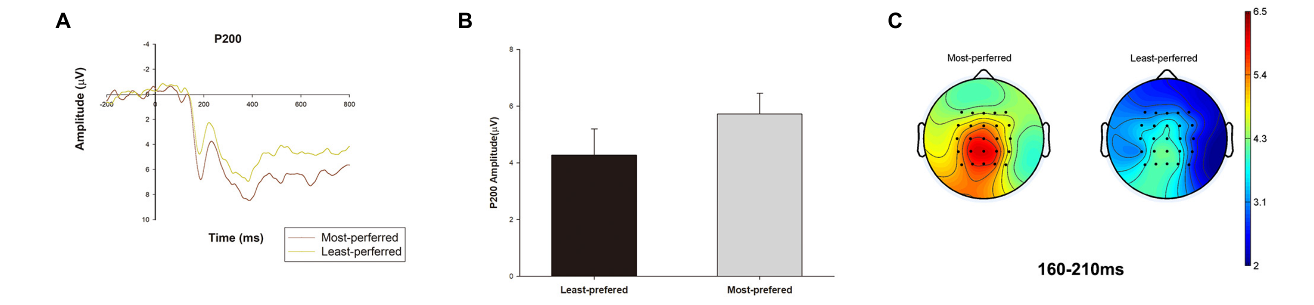

FIGURE 2 | P200 condition effect. P200 waveforms were averaged from the 16 subjects, and we pooled the data from C1, CZ, C2, CP1, CPZ, CP2, P1, PZ, and P2 electrodes. The time window was 160–210 ms for P200. **(A)** The ERP grand-average waveforms of P200 component in the most-preferred and the least-preferred product design conditions. **(B)** The bar chart reflecting mean amplitude of P200 in the most-preferred and the least-preferred product design conditions. Error bars indicate standard error. **(C)** Topographic maps of the most-preferred and the least-preferred product design conditions for P200 amplitude.

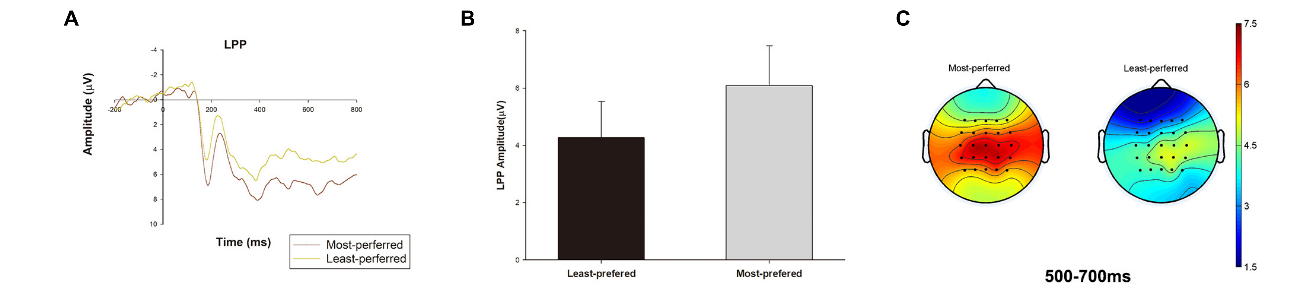

FIGURE 3 | The LPP condition effect. The LPP waveforms were averaged from the 16 subjects, and we pooled the data from C1, CZ, C2, CP1, CPZ, and CP2 electrodes. The time window was 500–700 ms for the LPP. **(A)** The ERP grand-average waveforms of the LPP component in the most-preferred and the least-preferred product design conditions. **(B)** The bar chart reflecting mean amplitude of P200 in the most-preferred and the least-preferred product design conditions. Error bars indicate standard error. **(C)** Topographic maps of the most-preferred and the least-preferred product design conditions for the LPP amplitude.

these brands [$F(4,2964) = 2.279$, $p > 0.05$). In addition, we found that the scores of the same T-shirt design were significantly different (the SD of the mean scores was 16.858), which indicated the importance of individualized experimental stimuli. Paired *t*-tests showed that the difference between consumers' average preference for the most- and least-preferred experience good designs was significant [(M most-preferred = 68.75, M least-preferred = 35.680), $t(15) = 13.369$, $p < 0.01$].

A pairwise *t*-test indicated that the P200 amplitude was larger for the most-preferred than for the least-preferred experience good designs [$t(15) = 3.331$, $p < 0.01$, M most-preferred = 5.717, M least-preferred = 4.273; 95% confidence interval [CI]: [0.520 2.367], **Figure 2**]. For the LPP, a paired *t*-test also indicated a significant difference between the most- and least-preferred experience good designs [$t(15) = 2.372$, $p < 0.05$, M most-preferred = 6.089, M least-preferred = 4.268; 95% CI: [0.185, 3.456], **Figure 3**].

Repeated measures analysis of correlations indicated that the P200 amplitude and average preference rating scores for the experience good designs were significantly positively correlated ($r = 0.553$, $p < 0.05$, 95% CI = [0.056 0.830]). The LPP amplitude and average preference rating scores for the experience good designs were also significantly positively correlated ($r = 0.606$, $p < 0.01$, 95% CI = [0.136, 0.853]). These results indicated a positive correlation between the P200 and LPP amplitude and the consumer preference rating scores, which implies that the higher the P200 and the LPP amplitudes were, the higher were the personal preference ratings for the product designs of experience goods.

DISCUSSION

This study investigated consumers' neural responses to the most-preferred and least-preferred experience good designs. Using personalized T-shirt pictures, we found that, compared to the least-preferred product designs of experience goods, the P200 and LPP amplitudes were consistently enhanced for the most-preferred designs. Furthermore, the mean amplitudes of P200 and the LPP were significantly positively correlated with the consumers' average preference ratings.

From a theoretical standpoint, compared to the study of Telpaz et al. (2015), which only demonstrated a positive relationship between an increased early ERP component (N200) and consumers' future choice (Telpaz et al., 2015), we demonstrated that, compared to viewing pictures of the least-preferred product designs, viewing pictures of the most-preferred experience good designs elicited larger amplitudes in early and late (P200 and LPP) ERP components. This may be because we focused on experience rather than on search goods.

Previous studies have shown that the late component, LPP, was associated with the arousal of emotional stimuli. For highly arousing emotional stimuli (whether positive or negative), the amplitude of the LPP was steadily increased as compared to neutral stimuli (Schupp et al., 2000, 2004). Minnix et al. (2013) have also showed that images with high-emotional arousal induce higher LPP amplitude than images with low-emotional arousal, while the LPP amplitude did not differ between images without emotional arousal (neutral objective images). In addition, other studies have also showed that the esthetic experience evaluation process includes two different stages: early impression formation and post-evaluation classification (Celaconde et al., 2013). P200 and the LPP can represent the early attention arousal and the late emotional cognition assessment, respectively (Parasuraman and Beatty, 1980). Based on these studies, it is believed that, for product designs with high emotional arousal, later ERP components will be enhanced. In the process of evaluating search good designs, consumers focus on search attributes (e.g., functions, shape, and dimensions). The emotional arousal level induced by these search attributes was lower than by the experience attributes. Therefore, there was no difference between the LPP component in the preferred and unreferred product conditions. Experience good designs are related to symbolic and esthetical dimensions of product design, which are related to emotional experience and arousal (Homburg et al., 2015). This explains why the amplitude of early and late ERP components were both enhanced for experience goods.

For the early components, this study indicated that, compared to viewing the pictures of the least-preferred experience good designs, viewing pictures of the most-preferred designs elicited a larger P200, rather than N200, amplitude. This result indicates the role of early attention in the evaluation of experience good designs. Previous studies have indicated that early ERP components (such as P200) reflect the perceptual processing of visual stimuli (Parasuraman and Beatty, 1980); a larger degree of visual stimulation (such as the most-preferred product designs) evoked more attentional arousal. However, consumers who purchase search goods will more likely to consider the objective attributes (e.g., price and function) and economic rewards of these attributes (Huang et al., 2009). As search goods (attributes) that are not preferred by consumers will result in lower reward outcomes than they anticipated (Baker and Holroyd, 2011), the N200 component in the early stage will be enhanced to represent this mismatch (Pozharliev et al., 2015). Therefore, ERP amplitudes enhancement differed for search and experience goods. In addition, previous studies have indicated that P200 not only reflects the initial response to esthetic stimuli, but is also related to the subsequent approach and withdrawal behavior (Schapkin et al., 2000). For example, early neural activities (such as P200) were related to later subjective behavior during environmental risk evaluation (Qin and Han, 2009). These results support the conclusion that the P200 component was positively related to the subjective preference evaluation in our study.

As for the LPP, we found a more enhanced LPP amplitude at around 600 ms for the most-preferred product designs than for the least-preferred designs after exposure to experience good designs. We also found that the LPP amplitudes were positively correlated to consumers' personal preference scores. Based on a previous study (Bradley et al., 2007), we can infer that the most-preferred product designs of experience goods evoked greater emotional arousal than the least-preferred designs. Besides the esthetic dimension, the enhancement of the LPP component in this paper may also be related to the symbolic dimension of experiential product designs, because the symbolic meaning of the product design is also related to affective product attributes (Homburg et al., 2015). The increased LPP amplitude also reflected motivated attentional processing and motivational intensity (Ferrari et al., 2011), implying enhanced allocation of relevant resources to promoting and speeding up the processes leading to a suitable response to the stimuli (Lang et al., 1997). Previous studies have shown that enhanced LPP reflects the increased positive emotional motivation for a preferred brand and represents a positive buying willingness for the brand (Bosshard et al., 2016). Therefore, in line with previous studies, we observed that LPP was related to behavioral responses to product designs of experience goods.

At a practical level, this study established that the two ERP components, P200 and the LPP, were positively correlated with the evaluation of experience good designs, implying that ERPs can be used to predict consumers' personal preferences for product designs of experience goods. In addition, as this study used the personalized experimental stimuli, the results can also help to understand the consumer's evaluation of personalized product designs. This study further indicated that ERPs can be used to predict consumers' preference for experience good designs, without them making actual decisions. EEG signals are of great use when rating data are not available or are limited and may help to reduce responses and inference biases in a practical context.

Compared to previous studies, we used subjective rather than objective ratings (for example, sales or other measures) to assess consumers' preferences for experience good designs. Such subjective measures have been recommended to capture the personal and subjective nature of esthetic evaluation (Chatterjee et al., 2009; Conway and Rehding, 2013; Pearce et al., 2016). We assigned experimental stimuli based on the individual preferences of the participants. We found that participants' preferences for the same experience product design varied greatly. Therefore, if we had not used personalized materials, we could not have observed differences in the EEGs during the process of evaluating experience product designs. In addition, by using passive viewing rather than direct assessment of experience good designs, our results indicated that the ERP components evoked by experience good designs were related to consumers' preferences. These results are consistent with those of previous studies, which have indicated that even without paying explicit attention to pictures (not required to provide assessment), participants can still exhibit a neural response to the pictures (Chatterjee et al., 2009; Pozharliev et al., 2015).

This study had some limitations. First, although this study focused on experiential products, we only used T-shirts as experimental stimuli. Whether the results of this study can be extended to other experience goods requires further attention. Second, in order to capture consumers' subjective and personalized characteristics of product design evaluation, we used the subjective preference scores of each participant to classify experimental stimuli into two groups. Although we used various methods to maximize the accuracy of subjective measurement, a social desirability bias may still remain. Third, we did not directly compare the ERP response between experience and search goods. Although we focused on experiential products, the concept of experience products was proposed relative to search goods (Nelson, 1970, 1974). It may be better to compare the differences in ERP responses between the two types of product designs directly.

CONCLUSION

This study explored individuals' neural responses to experience good designs and their relation to personal preferences. Using personalized T-shirt designs as stimuli, the results indicated that two ERP components, P200 and the LPP, were both enhanced in response to the most-preferred product designs of experience goods as compared to the least-preferred designs, when participants simply viewed the product designs without making actual decisions. Both of the ERP components were positively correlated with the consumers' preference scores for these experience good designs. The results indicated that ERP signals may provide important information regarding consumer preferences for experience good designs and can shed light on why consumers like customized products.

ETHICS STATEMENT

This study was carried out in accordance with the recommendations of the Ethics Committee of the Academy of Neuroeconomics and Neuromanagement at Ningbo University with written informed consent from all subjects. All subjects gave written informed consent in accordance with the Declaration of Helsinki. The protocol was approved by the Ethics Committee of the Academy of Neuroeconomics and Neuromanagement at Ningbo University.

AUTHOR CONTRIBUTIONS

YM made substantial contributions and participated in all aspects of the paper, conducted the experiment, analyzed the data, and wrote the manuscript. JJ and WY made substantial contributions to the work and participated in all aspects of the paper. WZ and ZX participated in the data acquisition and data interpretation stage. QM oversaw the study and managed every part of research. All authors read and approved the final manuscript.

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Things Become Appealing When I Win: Neural Evidence of the Influence of Competition Outcomes on Brand Preference

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Against the background of an increasingly competitive market environment, the current study aimed to investigate whether and how victory and defeat, as two critical factors in competition outcomes, would affect consumers' preference of unfamiliar brands. In the experiment, participants' status of victory or defeat was induced by a pseudo-online game, followed by a main task of brand preference rating. Using the precise and intuitive attributes of neuroscientific techniques, we adopted event-related potentials to analyze brain activity precisely during brand information processing when individuals experienced victory or defeat. Behavioral data showed that individuals had a stronger preference for unfamiliar brands in victory trials than in defeat trials, even if the brand was completely unrelated to the competition; this indicated a transfer of valence. Three emotion-related event-related potential components, N1, P2 and later positive potentials, were elicited more negatively in victory trials than in defeat trials, indicating the existence of incidental emotions induced by victory or defeat. No significant correlation was found between any pair of ERP components and preference scores. These results suggest that the experience of victory and defeat can evoke corresponding incidental emotions without awareness, and further affect the individual's preference for unfamiliar brands. Therefore, playing a game before presenting brand information might help promote the brand by inducing a good impression of the brand in consumers.

Keywords: brand preference, victory and defeat, emotion, event-related potentials, neuromarketing, neuromanagement

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INTRODUCTION

In modern society, competition between two or more organisms is ubiquitously present, ranging from economic competition and an arms race between countries, to rivalries among colleagues and schoolmates. Cruelly, victory and defeat always accompany competition, which may have an impact on an individual's attention (Sun et al., 2015), perception (Yu et al., 2017), emotion (Aviezer et al., 2012, 2015), confidence (Hsu and Wolf, 2001), and even sense of control (Burger, 1989). This would further result in numerous subsequent behavior changes, such as affecting the individuals' enthusiasm to participate in a contest (Rutte et al., 2006).

Considering the broad cognitive and behavioral impact from victory and defeat, consumer behavior studies have begun to pay attention to the influence of competition outcomes on consumers' mental status and decision-making process (Gronmo, 1988; Dalton, 2008; Sivanathan and Pettit, 2010). For instance, when participants were given false feedback on tests of their intelligence, those with a low IQ test result increased their willingness for self-expression consumer behavior, such as selecting expensive items, products, and shops (Dalton, 2008). Sivanathan and Pettit (2010) also found that negative test feedbacks induced consumers to bid higher for limited edition photographs. Therefore, consumers' experience of failure strengthened compensatory consumption, based on their need for improving self-esteem.

However, with the developing global integration of technology and the increasingly fierce market competition, it is becoming more difficult to gain predominance solely based on product differences because products have become more homogeneous. In this setting, brand awareness, which plays a key role in consumer behavior via information involving symbolic and systematized representations, memory, judgment, and inference (Loken, 2006; Jin et al., 2015), is becoming a critical factor affecting consumer behavior. Once the preference for a brand is determined, it tends to endure, be unaffected, and more importantly, is not easily replaced. As one of the main metrics for brand awareness, brand preference has been proven to predict consumer's brand evaluation, brand choice, as well as purchase intention and behavior (e.g., Priester et al., 2004; Fazio and Petty, 2007). Thus, whether competition outcome would affect brand attitude is an important topic; however, few studies have addressed this issue. Moreover, the psychological process of developing consumers' "favor" and "disfavor" should receive attention, so that brand preference can be strengthened.

Accordingly, the current study aimed to investigate the influence of competition outcome on brand preference and determined the process of its formation. Therefore, the current study first induced a victory or defeat experience by means of a competition, followed by the major task of brand preference rating. Questionnaires and behavioral experiments are two primary measurements used in research concerning brand preference. These subjective self-report instruments solely rely on participants' thoughts and description, yet many factors affecting human behaviors cannot be assessed by human conscious awareness (Zaltman, 2002). Furthermore, surroundings and social desirability would also distract from a preference-rating task, resulting in an expectation effect and manifesting as bias between the obtained results and the real mental process (Camerer et al., 2005). To address this issue, neuroscientific methods, such as event-related potentials (ERPs), may be a way to obtain unbiased and objective results. Therefore, we adopted ERP to determine the fundamental patterns of brain activity during brand information processing, while an individual is experiencing victory and defeat, more precisely. In this case, we could infer the neural dynamics and further explore factors that potentially mediate the victory/defeat experience as well as the consumer's attitude toward unfamiliar brands.

The ABC model of attitudes (Breckler, 1984) suggests that emotion might be one of the influential factors. According to this model, human attitude structure is generally divided into three main component: consumers need to know the commodity first (cognitive), which generates the corresponding emotion (affect), and then make a final consumption decision (behavior) (Breckler, 1984). The indispensable role of emotion in this model has also been supported by empirical research. For instance, Harlé and Sanfey (2007) found that subtle emotions, such as sadness and amusement, induced by short movie clips, could effectively bias the decision-making process in the Ultimate Game. Moreover, distinguishable incidental emotions, which are even unrelated to the immediate situation, would also lead to different product evaluations (Kim et al., 2009). In analogy, in the current study, we inferred that consumer behavior might, to a large extent, be affected by emotional arousal when facing an unfamiliar brand. To reveal the subtle emotion distinction, the ERPs N1 and P2, during the early processing phase, and late positive potentials (LPPs), in the later cognitive phase, which could be evoked at different amplitudes by positive and negative emotional stimuli, were adopted as the ERP indicators in the current study.

During information processing, N1 has been considered as the earliest component induced by emotional information; the amplitudes of this ERP differs notably for positive and negative emotional stimuli (Carretié et al., 2003). N1 is evident at frontal−central sites at approximately 130−150 ms after the onset of an emotion stimulus (Keil et al., 2001). P2 is also an early component that peaks positively at 250−350 ms after the onset of a stimulus, and has been claimed to be a sensitive index of attention distribution, with a higher P2 amplitude elicited by negative stimuli than with positive or neutral stimuli (Carretié et al., 2001; Huang and Luo, 2006; Wang et al., 2012). In the later processing phase, LPP, which is associated with evaluative categorization, generally begins around 300−500 ms after the onset of a stimulus and lasts for hundreds of milliseconds (Cuthbert et al., 2000; Schupp et al., 2000; Wang et al., 2016); it is elicited with greater amplitudes by negative rather than positive stimuli (Hajcak and Olvet, 2008; Ma et al., 2017). We therefore utilized N1, P2, and LPP to examine the role of emotions underlying the whole process from competition outcomes to brand preference.

In the current study, participants were asked to complete a time-estimation task as a means of generating a victory or defeat experience, and then their degree of preference for an unknown brand was assessed. Both behavioral and ERP data were collected to investigate whether victory or defeat experience would affect the individuals' preference for strange brands. Behaviorally, we assumed that individuals who had experienced victory would demonstrate a stronger preference for an unrelated and unknown brand than individuals who had experienced defeat. Neurologically, the victory experience was expected to induce a more positive emotion, thus a more negative N1, P2, and LPP might be evoked by a victory than by a defeat experience. In addition, the correlation between brand preference rating and brain activities of emotion induced by victory or defeat experience was also considered. If a correlation was evident, brand preference would change linearly with emotion intensity; alternatively, the increase in the degree of emotion intensity would not accompany a widened bias for brand preference.

MATERIALS AND METHODS

Participants

Twenty-one graduate and undergraduate students (11 females; mean age 23 years) were paid to participate in this experiment. None had a history of neurological problems and all had normal or corrected-to-normal vision. The participants provided written informed consent in accordance with the Declaration of Helsinki prior to the experiment, and all experimental procedures were approved by the local institutional ethics committee of the Academy of Neuroeconomics and Neuromanagement at Ningbo University.

The sample size of the study was determined via a "distribution-based approach to test selection" in G*Power 3 (Faul et al., 2007; Nosek et al., 2009; Minichilli et al., 2010). Given a large effect size (f = 0.40; η_p^2 = 0.14), a power of 0.95, and an alpha level of 0.05, we found that a paired sample t-test would be more powerful than a within-subjects F-test. Thus, we used the within-subject F-test for consideration of power. The power analysis ultimately yielded an estimated sample size of 18. Furthermore, considering drop-out and exclusion, we decided to enroll 24 individuals. Eventually, the data of three participants were discarded due to excessive recording artifacts, resulting in a valid sample size of 21 for analysis.

Stimuli

Stimuli were presented on a gray background (80, 80, 80) monitor of a 19-inch computer (100-Hz refresh rate). Two types of stimuli were adopted in the experiment. In the time estimation task, we used a 3.0° × 3.0° white square, always positioned in the center of the screen. In the brand preference rating task, all 40 logo images from the study by Ma et al. (2017) were used. Each logo image comprised English letters representing the brand name and an earphone picture (see **Figure 1**). The earphone picture was the same across the 40 logos, occupied a 7.0° × 7.0° square area, and were also positioned in the center of the screen. These brand logos do not exist in real life, and no participant in either the study by Ma et al. (2017) or the present study reported having ever seen any of them. In order to minimize the influence of luminance, contrast, and color saturation difference, all logo images were gray-processed using Photoshop®.

Design and Procedure

When the participant entered the laboratory, he/she was told to compete with another participant as the opponent in a LAN-based game. Their communication was restricted to a greeting when they first met at our laboratory. In the formal experiment, the "LAN-based game" was actually an offline game, and the opponent was one of the experimenters, in disguise, who would not in fact play the game. These manipulations were used in order to control the participant's winning percentage to guarantee sufficient valid trials for ERP analysis.

Participants were seated in an electrically shielded and sound-attenuated recording chamber at a distance of 70 cm from the monitor. We used Presentation® software to control the stimulus presentation and response acquisition. Participants were given clear instructions on how to perform the experimental trials. The procedure is illustrated in **Figure 1**. Two tasks, the time-estimation task and logo preference-rating task, were set in sequence in each trial. First, the time-estimation task paradigm required participants to estimate an interval as accurately as possible. At the beginning of each trial, an instruction was presented for 2,000 ms to indicate the interval that needed to be estimated, followed by a white square indicating the onset of the time-estimation task. Participants were asked to press a button with their right index finger once they thought that the interval had elapsed. The square would then disappear, and be replaced by a progressing page to wait for the competition results, which lasted 2,000−3,000 ms. Feedback was then given visually, informing the participants whether they had won or lost, the estimated times, and the precision of both their own and their opponent's time estimations. As an example of a victory condition, the feedback information might be as follows: "You win! You estimated 1,918 ms, deviating from the actual interval by 82 ms; your opponent estimated 1,850 ms, deviating from the actual interval by 150 ms." In this frame, the participant's actual estimated time was given, while the opponent's estimated time was conditionally controlled by the program. In the victory condition, the opponent's absolute value of the estimated time deviation was larger than that of the participant (randomly generated from 50 to 400 ms); in the defeat condition, the opponent's absolute value of the estimated time deviation was smaller than that of the participant (randomly generated from 1 to 50 ms). The feedback information was presented for 5 s. After a blank interval of 1,000−1,500 ms, a brand logo image was displayed, indicating the onset of the second task. After a 1,000-ms display, a 5-point Likert scale was presented below the image, and participants were asked to rate their preference for this brand by pressing the corresponding numeric keys on the keyboard, from 1 (extreme dislike) to 5 (extreme like). The rating score would be shown in real time for participants to confirm by pressing the return key. No time limitation was set for the logo-rating task. The inter-trial interval was randomized from 2,000 to 3,000 ms. After all trials had finished, participants were asked if they were aware of the experimental objective and whether their emotion was aroused during the experiment. No one answered affirmatively to these questions, and the data of these participants were then used for analysis.

Each participant completed 80 trials in total, with 40 trials each in victory and defeat conditions. Forty logo images were randomly ordered; each appeared twice, separated by at least 20 trials. The experiment was divided into six blocks with 5-min breaks between them. Before the formal experiment, participants were given the opportunity to practice with other brand logos for at least 15 trials to ensure that they understood the instructions.

Electrophysiological Recording and Analyses

EEG recordings were made at 64 scalp sites by using Ag/AgCl electrodes mounted on an elastic cap. All recordings were made using the left mastoid reference, and the data were re-referenced offline to the algebraic average of the left and right mastoid

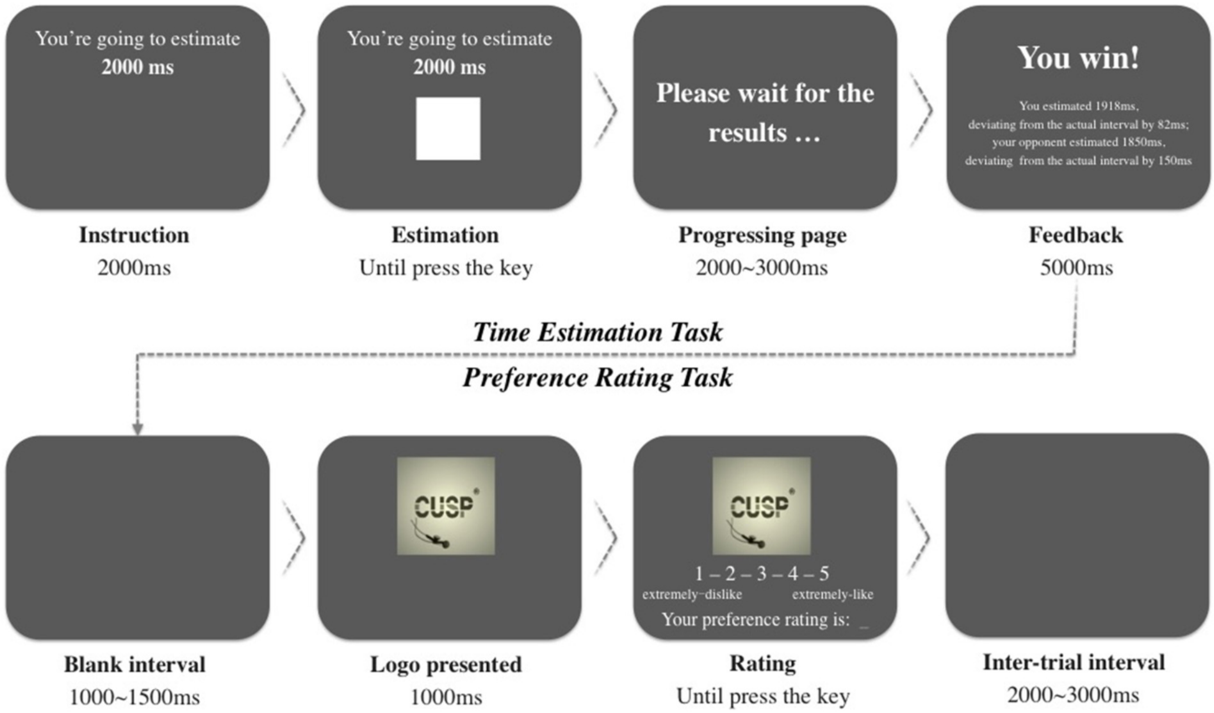

FIGURE 1 | An example of a trial with 2,000-ms estimation time in a victory condition, proceeding from left to right and top to bottom.

voltages. Vertical electro-oculograms (EOGs) and horizontal EOGs were recorded using two pairs of electrodes. One pair was placed above and below the left eye, and the other pair was placed at the outer canthus of both eyes. All inter-electrode impedances were maintained below 5 kΩ. The EEG and EOG signals were amplified by a SynAmps2 amplifier (Compumedics NeuroScan, Charlotte, NC, United States) using a 0.05- to 100-Hz band-pass filter, and were continuously sampled at 500 Hz/channel for offline analysis.

EEG data were analyzed using NeuroScan 4.3.1. The data were initially corrected for eye blinks by using a regression procedure, followed by digital filtering through a zero-phase shift (low pass at 30 Hz, 24 dB/octave). The EEGs were then segmented into epochs ranging from 200 ms before to 1,000 ms after the onset of the logo image for all conditions, and the epoch was baseline-corrected using a 200-ms interval prior to the presentation of the logo image. Trials with remaining artifacts exceeding ±75 μV in amplitude were rejected and excluded from analysis.

Paired sample *t*-tests were conducted on logo preference ratings between the victory and defeat conditions. Two-way repeated-measure analyses of variances (ANOVAs) were adopted to analyze the peak amplitudes of logo-onset N1 and P2, as well as the mean amplitude of LPP during the time-window of interest. Electrode sites in the midline frontal (F1, Fz, F2) and frontal−central (FC1, FCz, FC2) regions were selected for N1 and P2 analysis. To observe LPP, three electrode sites in the parietal region (P1, Pz, P2) were selected, and the amplitudes for the period 300−550 ms were averaged. For factors with more than two levels, the Greenhouse−Geisser correction (Epsilon) was used to adjust the degrees of freedom when necessary. Significant main effects ($p < 0.05$) were always followed by *post hoc* evaluations with a Bonferroni-corrected *p*-value. Pearson's correlation analyses were also used to assess the correlation between brand preference rating and brain activities of emotion induced by an experience of victory or defeat.

RESULTS

Behaviorally, the subjective logo preference rating was higher in the victory condition than in the defeat condition, $M_{victory} = 3.06$, $M_{defeat} = 2.89$, $t(20) = -2.48$, $p = 0.022$.

The ERP results are depicted in **Figures 2A–C**. At brain level, 6 (electrodes: F1, Fz, F2, FC1, FCz, FC2) × 2 (game results: victory, defeat) two-way ANOVA for peak amplitudes of N1 revealed a significant main effect of game results, $F(1,20) = 6.409$, $p = 0.020$, $\eta_p^2 = 0.243$, while the main effect of electrodes, $F(5,100) = 0.537$, $p = 0.603$, $\eta_p^2 = 0.026$, and interaction between the two variables were non-significant, $F(5,100) = 0.859$, $p = 0.436$, $\eta_p^2 = 0.041$. *Post hoc* evaluations confirmed that the averaged peak amplitudes of N1 for the victory condition, $M_{victory} = -3.743$, were more negative than those for the defeat condition, $M_{defeat} = -2.226$.

The peak amplitudes of P2 followed a similar results pattern as N1. A 6 (electrodes: F1, Fz, F2, FC1, FCz, FC2) × 2 (game results: victory, defeat) two-way ANOVA for peak amplitudes of P2 revealed a significant main effect of game results, $F(1,20) = 4.879$, $p = 0.039$, $\eta_p^2 = 0.196$, while the main effect of electrodes, $F(5,100) = 1.781$, $p = 0.190$, $\eta_p^2 = 0.082$, and interaction

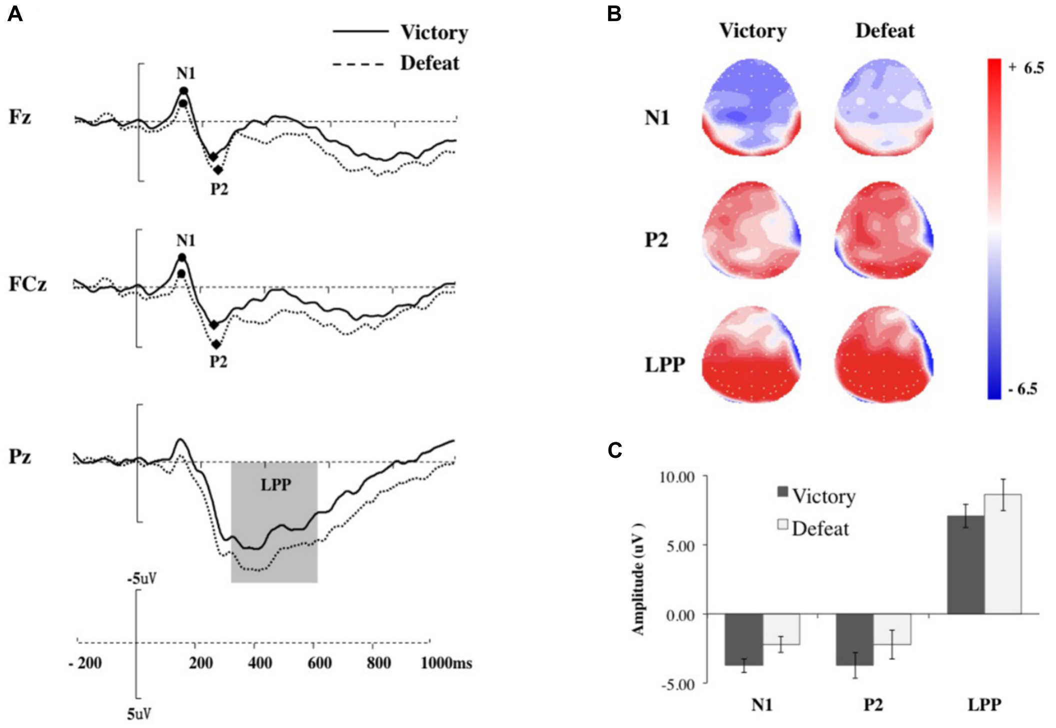

FIGURE 2 | Results of experiments. **(A)** Representative example: ERP waveform in Fz, FCz, and Pz (from top to bottom); **(B)** topographic maps in Victory and Defeat conditions for N1, P2, and late positive potential (LPP); and **(C)** the mean amplitudes of N1 in F1/F2/Fz/FC1/FC2/FCz, and P2 in F1/F2/Fz/FC1/FC2/FCz, and LPP in P1/P2/Pz, and the error bars represent one SEM.

between the two variables were non-significant, $F(5,100) = 0.918$, $p = 0.414$, $\eta_p^2 = 0.044$. *Post hoc* evaluations also confirmed that the averaged peak amplitudes of P2 for the victory condition, $M_{victory} = 4.363$, were more negative than those for the defeat condition, $M_{defeat} = 5.973$.

For LPP, 3 (electrodes: P1, Pz, P2) × 2 (game results: victory, defeat) two-way ANOVA results revealed a significant main effect of game results, $F(1,20) = 6.133$, $p = 0.022$, $\eta_p^2 = 0.235$. *Post hoc* comparisons showed a markedly more positive amplitude for the defeat condition than for the victory condition. Neither the main effect for electrodes, $F(2,40) = 1.642$, $p = 0.206$, $\eta_p^2 = 0.076$, nor the interaction between the game results and electrodes, $F(2,40) = 3.055$, $p = 0.058$, $\eta_p^2 = 0.132$, was statistically significant.

In addition, none of the correlations between preference rating and the mean amplitude of the selected electrodes or either N1, P2, and LPP in Victory and Defeat conditions were significant ($ps > 0.48$).

DISCUSSION

In the current study, a time-estimation task was adopted to prime victory or defeat, followed by a measurement of the individual's preference for unfamiliar brands. In this way, we investigated whether the experience of victory and defeat had an impact on brand preference, and assessed the evidence at brain activity level. Behavioral results showed that participants would have a relatively higher preference score for unfamiliar brands after victory trials than after defeat trials. At brain level, more negative N1, P2, and LPP amplitudes were elicited in victory trials than in defeat trials, indicating that individuals' brand preference was influenced by an incidental emotion induced by the experience of victory or defeat. Moreover, no significant correlation was found between any pair of ERP components and preference ratings.

Consistent with our hypothesis, behavioral data reflected that individuals had a relatively strong preference for unfamiliar brands after experiencing victory, even though the brand information had nothing to do with the competition itself. It could be inferred that the competition outcomes modulated the processing of brand information, manifesting as a transfer of valence.

Furthermore, the results for all investigated ERP components were compatible. A victory experience elicited a more negative N1 in the frontal and central electrode sites than a defeat experience. Previous findings had showed a relatively more negative N1 for emotional stimuli than for non-emotional stimuli, while the amplitudes of N1 for stimuli with positive and negative valences differed markedly (e.g., Carretié et al., 2003). Thus, it is possible that victory and defeat experiences would arouse opposite emotions, and then further induce different impacts on the preference for brands during the early processing phase.

For the sequential P2 component, a larger amplitude was found during the brand preference task after a defeat experience than after a victory experience. As a manifestation of negativity bias, P2 with larger amplitude reflects a greater attention distribution to negative stimuli (e.g., Carretié et al., 2001). Given this cognitive function of P2, the effects of significantly higher P2 amplitude after victory trials in the present study might be due to an induced positive emotion after a victory experience, which is in line with the inference for N1.

For LPP in the later processing phase, the higher central—parietal LPP amplitude found in this study was similar to that in many previous studies on LPP. For instance, a face showing a negative emotion would elicit a larger LPP than a face showing a positive emotion (Ma et al., 2017), demonstrating that faces with different emotional valence reflect differently in terms of LPP. Another study also found a numerically larger LPP for unpleasant than for pleasant pictures (Hajcak and Olvet, 2008). In our study, a similar LPP pattern implied that victory and defeat experiences might undergo an analogical implicit emotion regulation. Taken together, our results were highly consistent across three ERP components: experiences of victory and defeat elicited positive and negative emotions, respectively.

Combining the results of N1, P2, and LPP, we inferred that the initial perception of a new brand undergoes the following stages. A positive or negative emotion is first evoked by an experience of victory or defeat; then, attentional distribution is biased for the subsequent stimuli (even stimuli that are completely unrelated to the competition) during the maintenance period and finally affects the decision-making process. Specifically, in the current study, compared to the Defeat experience, the Victory experience would attract more attentional resources to process the sequentially emerging, irrelevant information, thus increasing its favorability and resulting in behaviorally higher preference scores. Considering the non-significant correlations between each pair of ERPs and behavioral data, we further inferred that such a preference bias only existed between different emotional valences, unrelated to the emotional intensity. Thus, the preference bias occurs when emotional arousal exceeds a certain threshold and is then maintained steadily, regardless of increased emotional intensity.

In line with the ABC model of attitudes (Breckler, 1984), both behavioral and ERP results suggest that competition outcomes would evoke corresponding emotions, which can be considered as incidental effects (Bodenhausen, 1993; Cohen et al., 2008), and then further influence the subsequent brand preference evaluation. Past research has indicated that incidental affect might be involved in various cognitive processes, including consumers' evaluation of products (Kim et al., 2009), decision-making (Harlé and Sanfey, 2007), and evaluation of brand extensions (Barone et al., 2000; Yeung and Wyer, 2005), mainly demonstrating an affect-congruent influence. Specifically, a good mood always accompanies positive appraisal, while a bad mood accompanies negative appraisal. For example, individuals being interviewed on a sunny day would mostly feel happy and report higher levels of life satisfaction than those being interviewed on a rainy day (Schwarz and Clore, 1983). Thus, positive emotion and behavior become connected due to their close temporal or spatial relationship, as will negative emotion and behavior. According to the "affect-as-information" hypothesis (Schwarz and Clore, 1983; Schwarz, 2012), both decision-related affect and decision-unrelated incidental affect have informational value that increases the cognitive availability of affect-congruent information, and impact the individual's judgment.

The ERP data from this study have proven that victory and defeat induce different incidental emotions, and bias the preference for the sequentially displayed brand, resulting in an assimilation effect. We considered this process under the "affect-as-information" hypothesis. Since human are not purely rational, we heuristically generate a feeling about an object. In the present study, in which all brands were completely unfamiliar, a sensible evaluation might be influenced only by the current emotional state, and the mood induced by the outcome of the immediately prior competition is the most likely source of this influence. Moreover, the transfer procedure from the incidental emotion to the target object was very rapid, because of the short interval between the time-estimation task and the brand preference-rating task, and may not have been realized by participants, as no awareness of emotional arousal was subjectively reported.

Thus, given the unconsciousness nature and rapid transfer of incidental affect, competition may be utilized as a potent tool to focus consumers' attention, lift their mood and gain positive brand attitude, without their awareness of the emotion's effect. In terms of marketing, competitions could accompany the brand of a commodity. In practical use, presenting information about a commodity or brand soon after winning in a pre-set game might help promote the commodity, by leaving consumers with a good impression of this commodity or brand. Furthermore, to benefit from the popular online consumption environment, commodity information can be presented along with individual or interactive online, rapid, and low-cost games as a new marketing approach, so that a positive emotion can be effectively evoked to obtain approval for the subsequently presented commodity, and increasing consumption potential. In an advertising case, such as a lottery, once the winnings are fixed, it would be better to choose that more individuals win a lower prize, rather than having the winnings divided among fewer people. In this way, more interest would be raised from potential clients, which would increase the overall preference for the brand.

AUTHOR CONTRIBUTIONS

WY and QM conceived and designed the experiments. WY, ZS, and TX performed the experiments and analyzed the data. WY and ZS compose the manuscript. QM is the principal investigator of the work. All authors reviewed and approved the manuscript.

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METHODS
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The Application of Mobile fNIRS in Marketing Research—Detecting the "*First-Choice-Brand*" Effect

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Recent research in the field of "neuro-marketing" shows promise to substantially increase knowledge on marketing issues for example price-perception, advertising efficiency, branding and shopper behaviour. Recently, an innovative and mobile applicable neuroimaging method has been proposed, namely functional near-infrared spectroscopy (fNIRS). However, this method is, in the research field of marketing, still in its infancy and is, consequently, lacking substantial validity. Against this background, this research work applied a convergent validity approach to challenge the validity of (mobile) fNIRS in the field of "neuro-marketing" and consumer neuroscience. More precisely, we aim to replicate a robust and well-investigated neural effect previously detected with fMRI—namely the "*first-choice-brand*" effect—by using mobile fNIRS. The research findings show that mobile fNIRS appears to be an appropriate neuroimaging method for research in the field of "neuro-marketing" and consumer neuroscience. Additionally, this research work presents guidelines, enabling marketing scholars to utilise mobile fNIRS in their research work.

Keywords: fNIRS, first-choice-brand effect, "neuro-marketing", consumer neuroscience, shopper neuroscience, neuroimaging

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INTRODUCTION

During recent decades, substantial milestones have been passed by marketing scholars moving marketing research forward (Eisend, 2015). Although this accumulation of knowledge has increased scholars and practitioners understanding, some marketing issues remain unsolved and might not be explorable using existing marketing methods (Zaltman, 2000; Eisend, 2015). To account for the diminishing utility of existing marketing methods (Eisend, 2015), scholars integrated innovative methods from cognate disciplines. Notably, the discipline of consumer neuroscience, in a business context also known as "neuro-marketing" (Hubert and Kenning, 2008; Harris et al., 2018), promises to substantially increase knowledge of marketing issues, for example price-perception, advertising efficiency, branding, purchase and shopper behaviour (e.g., Kosslyn, 1999; Kenning and Plassmann, 2005; Knutson et al., 2007; Plassmann et al., 2015; Falk et al., 2016; Kühn et al., 2016; Barnett and Cerf, 2017). This progression is predominantly driven by the belief that the utilisation of neuroscientific methods will add supplementary information to existing concepts and theories (Zaltman, 2000; Kenning and Plassmann, 2005; Plassmann et al., 2015). Fortunately, marketing research can greatly benefit from methodological progress in the research field of neuroscience. Mainly because, just recently, a novel neuroimaging method, namely mobile, functional near infrared-spectroscopy (fNIRS), emerged (Kopton and Kenning, 2014).

fNIRS is a relatively new, non-invasive neuroimaging technique that utilises near-infrared light sources able to penetrate human tissue (Ferrari and Quaresima, 2012). More precisely, (mobile) fNIRS uses specific wavelengths of light (760 and 850 nm) to provide a measurement of cerebral oxygenated (oxy-Hb) and deoxygenated haemoglobin, which are the main absorbers of near-infrared light (Kopton and Kenning, 2014), allowing the indirect quantification of neural activity to be measured. There are several fNIRS technologies applied (for further information please see: Scholkmann et al., 2014; Torricelli et al., 2014; Brugnera et al., 2018). In this research work, we used one of the most commonly utilised fNIRS technology, namely the continuous wave (CW) method, which allows to compute changes in oxygenated, deoxygenated and total haemoglobin concentrations from a calculated baseline (Torricelli et al., 2014). There is profound evidence that the fNIRS signal correlates significantly with the functional magnetic imaging (BOLD) signal (Fishburn et al., 2014; Masataka et al., 2015). The spatial resolution and penetration depth of mobile fNIRS is dependent upon the distances between light sources and detectors but generally capable of imaging depths of up to 2 cm (McCormick et al., 1992). This allows the measurement of neural activity in brain regions such as the prefrontal cortex (PFC), which plays a crucial role in consumers cognitive processing such as for example buying decisions (Deppe et al., 2005, 2007; Gonzalez et al., 2005; Knutson et al., 2007; Schaefer and Rotte, 2007; Plassmann et al., 2008; Quaresima and Ferrari, 2016; Goodman et al., 2017).

However, although previous research indicated the validity of fNIRS as a neuroimaging method in various scientific disciplines (Fishburn et al., 2014; Naseer and Hong, 2015; Kim et al., 2016; Werchan et al., 2016), to date, there is very little evidence supporting its utilisation in (neuro-)marketing research.

This is surprising given the fact that especially the application of the *mobile applicable* version of fNIRS might have the potential to overcome or at least reduce one of the major concerns of most neuroimaging techniques—it's immobility (Arnsten and Goldman-Rakic, 1998; Miyai et al., 2001; Atsumori et al., 2010; Funane et al., 2011; Szalma and Hancock, 2011; Yoshino et al., 2013; Boksem and Smidts, 2015).

However, because mobile fNIRS is still in its infancy, at least in the research field of marketing, this appealing method is lacking substantial validation. To address this issue, we applied a convergent validity approach to challenge the validity of mobile fNIRS. In particular, we strive to replicate a robust and well-investigated neural effect, previously detected with fMRI—namely the "*first-choice-brand*" effect—by using mobile fNIRS.

PROOF OF CONCEPT—THE MOBILE fNIRS VALIDATION APPROACH

The fact that the validity of mobile fNIRS has, to the present day, never been conventionally challenged in marketing research might be one reason for its limited utilisation. It is, however, fundamental that every novel method provides evidence of its validity specific to the scope of application. When discussing the concept of validity, it is essential to understand that *validity*, in a general sense, determines whether the research method truly measures that which it was intended to measure (Golafshani, 2003). However, in the literature there is a distinction between different kinds or "concepts" of validity that are (Gravetter and Forzano, 2003):

(i) the *predictive validity* which is demonstrated when a measurement accurately predicts behaviour according to a theory;
(ii) the *construct validity* which requires that the measurements obtained from a measurement procedure behave exactly the same as the variable itself;
(iii) the *divergent validity* which is demonstrated by using two different methods to measure two different constructs, accordingly there should be no or only a little relationship between the measurement obtained from the two different constructs when they are measured by the same method; and
(iv) the *convergent validity* which is demonstrated by a strong relationship between the scores obtained from two different methods of measuring the same construct (Gravetter and Forzano, 2003).

That said, it should be evident that scholars can choose from a set of validation approaches. For example, to validate mobile fNIRS scholars can follow the predictive validity approach (i), hypothesising that mobile fNIRS is able to quantify a particular neural brain activity based on a stimulus presented. Scholars could therefore assume, based on literature and theory, that visual stimuli lead to neural brain activity in the visual cortex, by testing this hypothesis utilising mobile fNIRS, scholars will be able to make an assumption about the validity of its utilisation.

By utilising the construct validity approach (ii), scholars can validate a neuroimaging method such as mobile fNIRS by showing that the same method can differentiate between two different and well investigated scientific constructs. Scholars could therefore, based on the knowledge that vision and motoric processes are located in different brain regions, indicate that it is possible, by means of mobile fNIRS, to distinguish neural cortical activity of visual and motoric stimuli, investigating the same construct namely neural activity. Consequently, depending upon the stimulus only one related brain region should be activated, allowing a proposition to be made about the operating principles of mobile fNIRS.

Moreover, scholars might choose to explore the validity of a neuroimaging method by utilising a divergent validity approach (iii), comparing two different deviating methods investigating two different entities. As a result, both methods should have contradictory outcomes.

Finally, in order to validate mobile fNIRS in a specific scope of application (as for example in the field of marketing), scholars could choose for a convergent validity approach (vi), replicating a robust and previously explored (neural) effect whilst employing an existing and already validated neuroimaging technique. By applying the same research paradigm as used in a previous research work, scholars could compare data acquired with an innovative and a validated (neuroimaging) method, verifying the innovative methods in the scope of application whilst exploring an existing, validated entity.

Taking the aforementioned concepts into account, we chose the convergent validity approach in order to explore whether mobile fNIRS is a suitable neuroimaging method also for marketing research and consumer neuroscience. The reason for this relies on the unique characteristics of the marketing relevant, neural effect of the "*first-choice-brand*" (Deppe et al., 2005). Based on its two interrelated sub-effects, the "*first-choice-brand*" effect is capable of providing information about potentialities as well as limitations directly related to mobile fNIRS and its technical capabilities, e.g., when it comes to measure subjacent brain regions. Insights that are solely explorable whilst utilising a convergent validity approach.

Consequently, based on scientific evidence and based on the technical capabilities of mobile fNIRS, we aim to *partly* replicate the "*first-choice-brand*" effect (Deppe et al., 2005; Koenigs and Tranel, 2007).

This specific brand-related effect, was first reported by Deppe et al. (2005), indicating that participants have distinctive neural activity in brain regions of the PFC whilst making a binary buying decision when their favoured brand (*first-choice-brand, FCB*) is involved. The "*first-choice-brand*" effect, which will be discussed in the next section, was found in several subsequent studies and seems to be a robust neural effect.

THEORETICAL BACKGROUND—THE "*FIRST-CHOICE-BRAND*" EFFECT

In essence, the "*first-choice-brand*" effect consists of two interrelated sub-effects. The *first sub-effect* is characterised by an increased neural activity in the ventromedial PFC (vmPFC), a subjacent medial brain region involved in processing of emotions, episodic memory retrieval and self-reflection during decision making (Deppe et al., 2005), displaying self-referential processes during first choice brand decision-making. The *second sub-effect* is characterised by reduced neural activity in the dorsolateral PFC (dlPFC), a brain region generally associated with working memory, inductive reasoning, planning, cognitive control, strategy-based reasoning, judgments and reasoning-based decision making (Braver et al., 1997; Courtney et al., 1997; Pochon et al., 2001; Kroger et al., 2002; Manes et al., 2002; Raye et al., 2002; Curtis and D'Esposito, 2003; Deppe et al., 2005). The reduced neural activity of the dlPFC might, potentially, indicate that strategy-based reasoning and judgments are reduced when participants are exposed to their favoured "*target*" brand compared to non-preference decision making trials (Deppe et al., 2005; Koenigs and Tranel, 2007; Schaefer and Rotte, 2007), allowing the consumers to take a quicker, straightforward and less complex decision when their individual target brand is present—a neural effect which is also called cortical relief effect (Kenning et al., 2002).

Based on the technical parameters of mobile fNIRS, in particular its spatial resolution and penetration depth (McCormick et al., 1992), mobile fNIRS is not capable of measuring subjacent medial brain regions lying deep in the brain. Consequently, we do expect that mobile fNIRS is solely able to partly replicate the "*first-choice-brand*" effect, namely only the *second sub-effect*. Against this background, we investigate the following hypotheses:

- H_1: mobile fNIRS is capable of measuring decreased neural activity in the dlPFC when consumers' decision making is associated with their first-choice-brand.
- H_2: mobile fNIRS is not capable of measuring increased neural activity in the vmPFC when consumers' decision making is associated with their first-choice-brand.

METHOD

Participants

In order to empirically test our hypotheses, a total number of $N = 42$ (Friston, 2003) right-handed (e.g., Toga and Thompson, 2003), female household running participants was recruited in order to take part in a fNIRS-experiment at University of Düsseldorf, Germany (M = 38.07, SD = 11.13 years of age, M = 1,725.49, SD = 879.28 net income in Euro). With regard to the fact that women are more frequent customers of grocery retailers and are, therefore, more frequently exposed to brand related decisions, only household running, female participants were recruited for this experiment (Rampl et al., 2012). All participants had normal vision and no history of neurological disorder and were informed about the nature of the experiment as well as the operating mode of mobile fNIRS, before the written informed consent was signed[1]. All subjects gave written informed consent in accordance with the Declaration of Helsinki. Subsequently, to increase their involvement, participants were requested to imagine that acquaintances had asked them to buy a high-quality filter coffee for their cream-tea appointment at the weekend. As they wanted to make a good impression, the participants needed to choose, whilst making their buying decision, the coffee

[1]Mobile near-infrared spectroscopy is a non-invasive method, simply projecting (near-infrared) light through the sculp. It is therefore with no advantages or disadvantages associated. Moreover, the utilised stimuli material integrated only coffee brands to which participants are confronted in every German grocery store. Consequently, an ethical approval for conducting the given experiment was not necessary. However, it should be evident that the experiment was conducted according to existing ethical standards (APA's Ethics Code and in compliance with the Declaration of Helsinki). Therefore, before the experiment started, participants were informed about the nature of the experiment as well as the operating mode of mobile fNIRS. Subsequently, participants were asked if they would like to voluntarily participate in the experiment and informed that they can stop the experiment at any time without any reasons, consequences and/or disadvantages.

brand which had, in their opinion, the highest quality. After completing the experiment, participants were asked to sort all coffee brands according to their preferences and buying intention. Based on the individual ranking, the selection of the target brand group (TBG) and the diverse brand group (non-TBG) was performed (Deppe et al., 2005). Only participants who rated the target coffee brand (the market leader) as their favourite brand, were assigned to the TB-group. This is essential in order to analyse the data, since the reduced dlPFC activity is only hypothesised for the TBG in comparison to the non-TBG. Furthermore, in post-experiment-interviews participants were enquired about their (filter coffee) shopping behaviour, asking if they are aware of the target brand as used in the experiment. This is inevitable to experience and consequently to display the "*first-choice-brand*" effect in the designed experiment, utilising mobile fNIRS. Only when participants indicated that they have never bought filter coffee before, they were excluded from further analysis. Following this procedure 10 participants were excluded, resulting in a sample size of $N = 32$ ($M = 37.97$, $SD = 10.97$ years of age) of which 16 participants selected the predefined target brand (T) as their favoured brand.

Task Procedure

The experimental task aims to examine if the presence of a filter coffee target brand, evoke a reduced neural, bilateral activity in brain regions ascribed to the dlPFC for participants who rated the target brand, *ex post*, as their favoured brand, measurable with the use of mobile fNIRS. Extending previous research (Deppe et al., 2005; Koenigs and Tranel, 2007; Schaefer and Rotte, 2007), participants were shown 100 different buying decisions scenarios in the presence or absence of a specific target brand (T) in which participants had to take a binary buying decision. "Jacobs Krönung" as German market leader was defined, *a priori*, as the target brand (T). The other brands were classified as diverse (D), resulting in a binary decision-making set of either TD (TD decision = target brand vs. diverse brands) or DD (DD decision = diverse brand vs. diverse brands) decisions. All trials were presented in a 10 × 10 event-related design, whereby in alternating order two types of trial composition were displayed. The compositions consisted either of 8 DD and 2 TD (20% TD) or 2 DD and 8 TD (80% TD) decisions, whereby the order of DD and TD decisions was randomised (please see **Figure 1**). For each of the 100 trials, participants had the option of two different coffee brands, which were presented on a computer screen, lasting for 3 s. The trials were separated from each other by means of jittered fixation cross lasting 4 to 6 s. For each single decision trial, participants were requested to decide mentally, were no manual response was required, which of the two displayed coffee brands they would like to buy.

No resting condition was implemented between the blocks, since participants needed merely 800 s (13.3 min) to complete the whole paradigm.

To assure the same environmental circumstances for every participant, the temperature and light conditions were kept equally and the background noises were kept to a minimum. Throughout the experimental task the experimenter left the room, but re-entered the room after participants indicated that they have completed the experimental task.

DATA COLLECTION, (PRE-)PROCESSING AND RESULTS

Data Collection

Optical signals were recorded on a two-wavelength (760 and 850 nm) continuous-wave fNIRSport-System (NIRx Medical

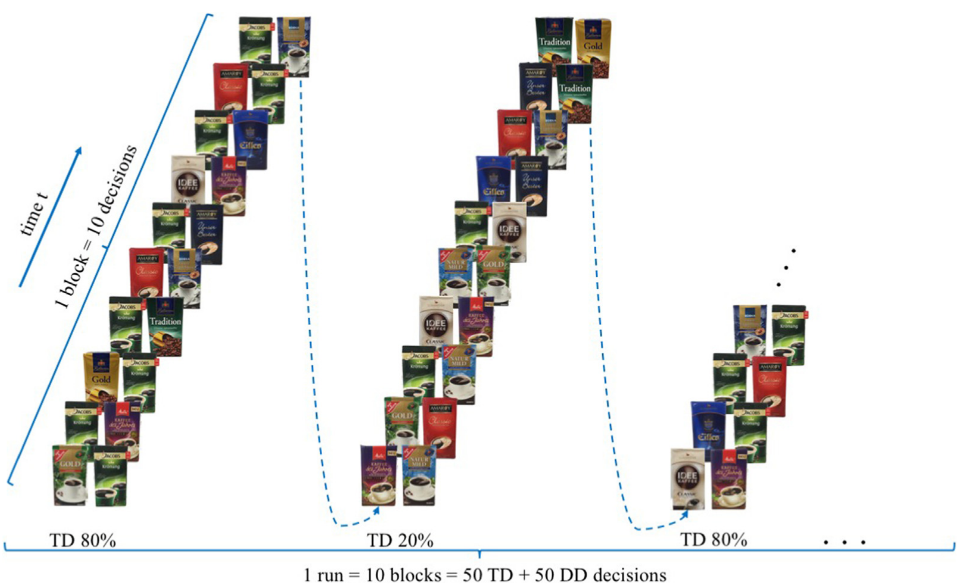

FIGURE 1 | Experimental design—modified version of the paradigm created by Deppe et al. (2005).

FIGURE 2 | Topographical layout—The topographical layout is a schematic representation of the measurements sites. It integrates 22 channel, each corresponding to a particular brain region of the three sub-regions of the prefrontal cortex, namely the dorsolateral prefrontal cortex (key channels 9 and 14), the orbitofrontal cortex (key channels 19 and 20) and the motor cortex (key channels 1, 3, 4 and 6).

Technologies, Berlin, Germany[2]). Data was collected from detectors in parallel at a sampling rate of 7.81 Hz. The optical channels were comprised of eight sources and eight detectors. Optodes and diodes are separated from each other by a distance of 3 cm in order to guarantee signal quality. Participants are fitted with a headband, covering most of the PFC in particular bilateral orbitofrontal cortex (OFC), bilateral dlPFC and bilateral premotor cortex. To ensure that the headband is located according to the anatomical brain structures of the participants, the craniometric point of the nasion, where the top of the nose meets the ridge of the forehead, was used to assure comparability between participants. Based on this configuration the "topographical layout," a schematic representation of the measurements sites, integrating 22 channels was designed, allowing to measure cortical neural activity of the PFC and its sub-regions as previously described (please see **Figure 2**). The NIRS-Star software package (version 14.2) was used to check for signal quality and data collection.

Data (Pre-)Processing

Before further analysis, the collected fNIRS raw data were pre-processed. Therefore, to smooth the raw data a band-pass filtered (high/low frequency filter) was applied in order to control for artefacts that might interfere with the measurement of the intended effects, as for examples the heartbeat or strong and abrupt head movements. The lower cut off frequency value was set to 0.01 Hz, whereas the higher cut off frequency value was set to 0.2 Hz.

Raw optical density signals were converted to haemoglobin concentration changes using the modified Beer-Lambert law (Delpy et al., 1988; Kocsis et al., 2006; Kopton and Kenning, 2014; Scholkmann et al., 2014) within the NIRx Software package (NIRx Medical Technologies, Berlin, Germany[2]). The parameters used to compute the haemodynamic states were set as follows, the distance of the first channel was set to 3 cm, the wavelengths were specified to values of 760 and 850 nanometre and the associated pathlength factor (DPT) was set to 7.25 for the wavelength of 760 nm and 6.38 for the wavelength of 850 nm, in accordance with commonly utilised values reported in literature (Essenpreis et al., 1993; Kohl et al., 1998; Zhao et al., 2002). As the oxy-Hb signal has been shown to correlate with cerebral blood flow better than the deoxygenated signal (Hoshi et al., 2001), the analysis concentrates on the oxy-Hb signal.

For every participant, a general linear model (GLM) was set up to model neural activity during the experimental task. The picture period, displaying the different coffee brands, was modelled separately for TD-trials and DD-trials, adding up to two event-related regressors together with an additional error term at the end ($Y_j = x_{j1}\beta_1 + x_{j2}\beta_2 + \varepsilon_j$). Each time course was further corrected for serial correlations such as physiological noise sources, modulating the stimulus onsets convolved by a haemodynamic response function (Worsley and Friston, 1995). No contrast was calculated for every participant individually (on within-subject-level). However, in order to investigate the estimated effects on group-level (between-subject-level), two groups were, based on the *ex post* conducted ranking of the coffee brands, created. Following the original article by Deppe et al. (2005) only participants who rated the target brand as their favourite brand, were assigned to the TB-group. T-contrasts were used to generate statistical parametric maps of activation by contrasting TD decisions of the TBG ($N = 16$) in comparison to TD decisions of the diverse brand group (non-TBG, $N = 16$). A t-contrast activation map of the neural PFC activity was plotted on a standardised brain. The activation map threshold was set to a p-value of $p < 0.05$ (please see **Figure 3**).

Data Results

As hypothesised, the results show significant bilateral cortical dlPFC decreased neural activity when participants take TD decisions, contrasting the TB-group and the non-TB group on a significant level of $p < 0.05$. Giving evidence for the second sub-effect, the cortical relief effect (Schaefer and Rotte, 2007; Kenning et al., 2002) in the TB-group, which was solely determined by the presence of the participant's most favoured target brand during binary buying decisions. More precisely, channel 16 ($t_{(31)} = -2.42$, $p < 0.05$, $d = -0.86$), channel 21 ($t_{(31)} = -2.74$, $p < 0.01$, $d = -0.97$) and channel 22 ($t_{(31)} = -2.49$, $p < 0.05$, $d = -0.88$), which are localised in dlPFC brain regions indicate a reduced neural activity when participants, who rated the target brand as their favoured brand, had to decide between a target and diverse brand in a binary buying decision task (please see **Figure 3**). Furthermore, as the effect size, measured

[2]http://nirx.net

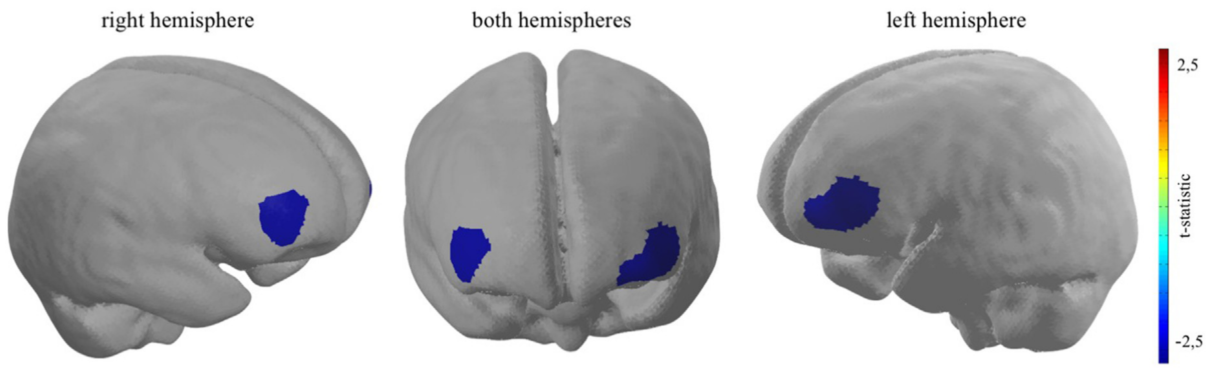

FIGURE 3 | Bilateral dlPFC decreased neural activity when participants who rated the target brand first are confronted with a TD decision. *Channel 16*: $t_{(31)} = -2.42$, $p < 0.05$; *channel 21*: $t_{(31)} = -2.74$, $p < 0.01$; *channel 22*: $t_{(31)} = -2.49$, $p < 0.05$.

with Cohen's *d*, exceed the value of 0.8 for all three reported effects, the magnitude of the measured effects can be defined as strong (Cohen, 1988). Moreover, confirming H_2 no significant increase in neural activity could be pictured in brain regions ascribed to the vmPFC, when the target brand was present, given participants ranked the target brand first (for detailed information, see **Supplementary Appendix 1.1–1.4**).

MOBILE fNIRS—A VALIDATED NEUROIMAGING METHOD?

The results of our study clearly support the assumption that mobile fNIRS has, in principle, the ability to assist scholars and marketers to enlarge knowledge, methods and analyses from extant approaches of consumer research, developing marketing theory and consumer research findings.

Whilst our research results indicated, in line with previous work (Deppe et al., 2005), that a participants' first-choice brand decreases the neural activity in brain regions ascribed to the dlPFC, simplifying the participants buying decision (Schaefer and Rotte, 2007), our research results also indicate some limitations of mobile fNIRS when it comes to measure subjacent brain region such as (parts of) the vmPFC (Koenigs and Tranel, 2007). Based on our results and previous research findings (McCormick et al., 1992) it should therefore be evident that mobile fNIRS is not always a suitable neuroimaging method or even a panacea; and cannot be applied when the research focus relies on, for example, subjacent brain regions. An example in this regard might be the measurement of emotional and perception processes such as price (fairness) perception (Knutson et al., 2007; Linzmajer et al., 2014). Given the fact that emotional and perception processes find its neural origin in "deeper" brain regions such as e.g., the hippocampus, the insula, the nucleus accumbens and/or the amygdala, mobile fNIRS with its technical capabilities, might currently not be able to shed light on these processes. Moreover, next to its spatial resolution, the temporal resolution of mobile fNIRS seems to be lower in comparison to for example electroencephalography (EEG), but seems to outperform the temporal resolution of fMRI (Wilcox and Biondi, 2015).

By keeping in mind that every neuroimaging method has its advantages and disadvantages, it should be noted that mobile fNIRS might have, in particular, the ability to: (1) minimise purchase and running costs; (2) increase the ecological validity, due to its potential mobile usage; and (3) exploit an extended sample, integrating participants that have been excluded earlier because of physical criteria (see Kopton and Kenning, 2014). Against this background, scholars and marketers should carefully select and verify the methodological instrument they would like to apply to answer a specific research focus. In the next section, we, therefore, aim to provide marketing scholars a short guideline of how to apply mobile fNIRS to their own research. In particular, we will try to answer the following questions: *If fNIRS is the answer, what should be the question? When should mobile fNIRS be applied in marketing research? And, finally, how should mobile fNIRS be applied (in a real world situation) and how to analyse the generated data?*.

MOBILE fNIRS—A SHORT GUIDELINE FOR MARKETING RESEARCH

If fNIRS Is the Answer, What Should be the Question?

As mentioned before, it should be evident that neuroscientific methods do not guarantee intended results and, consequently, increase the explained variance of a scientific entity. Instead, sometimes it is needless, costly and risky to utilise neuroscientific methods to answer a marketing related research question. Consequently, scholars need to be aware, *ex ante*, whether a neuroscientific tool has the potential to increase their understanding of a marketing related construct and can, therefore, add to existing marketing theories.

In order to illuminate whether mobile fNIRS can add to marketing research, scholars should ask themselves two additional questions, keeping the capabilities of a mobile fNIRS in mind: (i) How is information processing implemented within the brain and how is this related to a particular entity/ability? and (ii) when are particular processes and brain structures invoked? (Kosslyn, 1999).

These essential questions might be answered by conducting a comprehensive literature review in which scholars assimilate crucial information about their research focus and its connection to cognitive processes manifested in particular brain structures, combining both, the marketing and neuroscientific knowledge in one nomological network.

For example, if a marketing scholar is interested in emotional processes associated with a certain product characteristic (e.g., a car design), it should be evident that mobile fNIRS is, at the present time, not suitable to measure emotional processes, which find their neural origins in subcortical brain regions like the amygdala or the hippocampus (McCormick et al., 1992). Moreover, it is essential for marketing scholars to assure themselves that a given research question cannot be answered with existing marketing research methods, which might be more cost-effective (Ariely and Berns, 2010) and/or easier to administer (Dimoka et al., 2012).

As mobile fNIRS opens up the ability to gather neural data in a naturalistic environment, increasing the ecological validity, it should also be evident that the temporal resolution of mobile fNIRS might sometimes, depending on the research approach, be a limitation. This might especially be the case when a stimulus occurrence is uncontrolled in a naturalistic environment.

Against this background, marketing scholars should refrain from utilising mobile fNIRS when its application does not provide essential information above and beyond information quantifiable with existing measurements. Furthermore, they should refrain when no further information about the underlying cognitive processing mechanism, no information in regard to particular processes, the related brain structures and/or information about the temporal function of the process is provided.

When Should Mobile fNIRS be Applied in Marketing Research?

After the question "whether" mobile fNIRS generated knowledge can increase the explained variance of a marketing relevant entity is answered, scholars should ask themselves "when" to apply mobile fNIRS. Due to the rapid proliferation of neuroscientific methods and techniques, the absence of clear guidance how to conduct high-quality, user-oriented consumer neuroscience research and a possible ignorance of the added value of the integration of neuroimaging methods, it could become difficult for marketing scholars to decide, based on their research focus, which neuroscientific method to employ. So, scholars need to be aware about the technical capabilities of a given neuroscientific method. In line with this, neuroscientific methods could be categorised according to three dimensions, the temporal resolution, the spatial resolution and whether a neuroscientific method is portable or not.

Figure 4 compares the frequently applied neuroscientific methods, intends to summarise all three dimensions scholars need to be aware of, when applying neuroscientific methods.

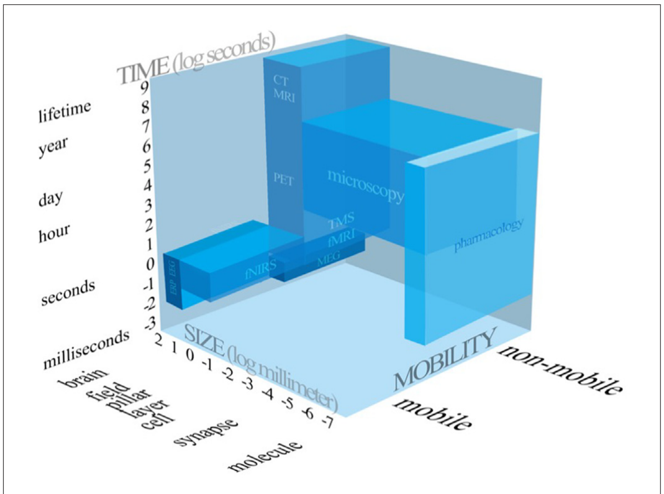

FIGURE 4 | Systematic representation of the neuroscientific tools applied in consumer neuroscience and related research fields.

Accordingly, scholars have to choose wisely, based on their research focus, whether to apply mobile fNIRS or not. As mentioned before, based on our research results it should be evident that mobile fNIRS is not able to measure the whole brain, but is capable of imaging depths of up to 2 cm (McCormick et al., 1992) of the human cortex. Consequently, subjacent medial brain regions cannot be measured by utilising mobile fNIRS. Hence, if the research focus rely on cognitive processes which are related to subjacent brain region, scholars might apply another neuroimaging methods, such as fMRI.

Even though, previous research indicated that fNIRS is capable of measuring brain regions such as for example the left anterior OFC (Ernst et al., 2013). There seems to be uncertainty regarding the technical capabilities of mobile fNIRS. Against this background, based on the fact that the previously mentioned brain regions are only vaguely defined and often incorporate wide areas of the PFC, it is particularly difficult for scholars to specify if mobile fNIRS is also capable of measuring subjacent brain regions which may interest them, such as the vmPFC. Consequently, based on the insufficient classification of cortical brain regions, our research work provides, based on our research results, a classification map (please see **Figure 5**), giving scholars the opportunity to decide if mobile fNIRS is able to measure a pre-defined region of the brain in which they are interested, or not. More precisely, a brain region such as the vmPFC might not be explorable (purple triangle) based on the technical capabilities of mobile fNIRS. Whereas brain regions which are located near the surface of the cortex, such as the OFC, alPFC and dlPFC, might be explorable with mobile fNIRS (red quadrant and blue circle).

How Should Mobile fNIRS be Applied (in a Real World Situation) and How Should the Generated Data be Analysed?

Mobile fNIRS has, in comparison to other neuroimaging methods, the advantage that it is portable administrable, allowing scholars to utilise mobile fNIRS in real world scenarios.

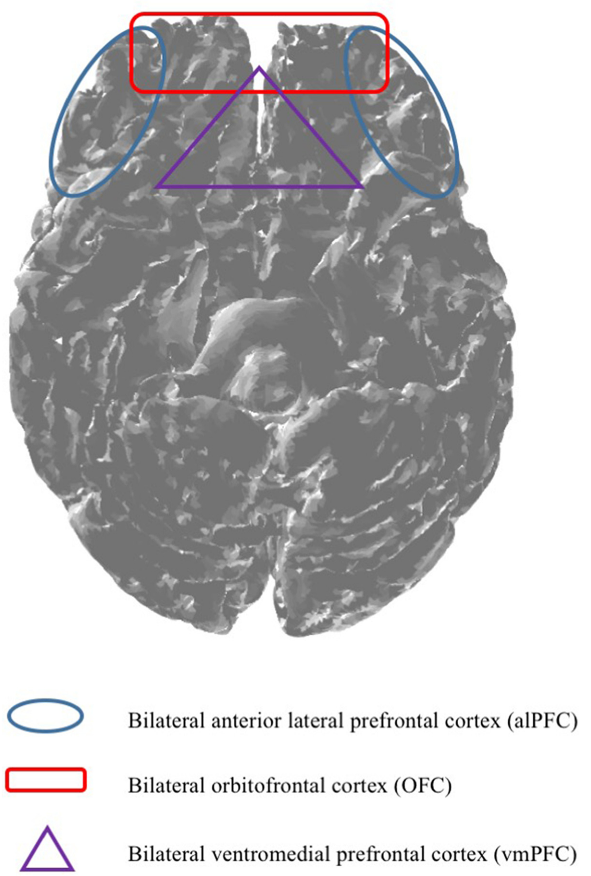

FIGURE 5 | Based on the technical capabilities, mobile fNIRS is capable of imaging depths of up to 2 cm (McCormick et al., 1992). Against this background, it is essential to predefine brain regions, *ex ante*, indicating which brain regions are measurable by utilising mobile fNIRS.

Therefore, in order to collect real world neural data to answer a particular research question, marketing scholars should follow a three-step approach.

The first step is the preparation of the experimental setting—the environment. This is indispensable based on the temporal resolution of mobile fNIRS, which requires the appearance of a stimuli for around 2 s to 3 s in order to measure the associated neural response. Given that the ultimate goal is to measure consumers in a real-world situation, such as at the point-of-sale (PoS), at the moment it is still necessary to prepare the environmental settings in order to account and control for potential confounding effects and to guarantee the perception of a stimuli that might be manipulated in a research paradigm.

The second step is the acquisition of data. In order to collect mobile fNIRS data to answer a particular research question, participants need to be equipped with a headband or a cap, comprising light sources and detectors that cover parts or the whole cortex. After the headband or cap is placed on the cortex scholars have to calibrate it to make sure that the signal quality is to their satisfaction. To check for the fNIRS signal quality, scholars could use several, mostly with the hardware delivered software packages[3]. Before starting the calibration to check for the fNIRS-signal quality, scholars should eliminate external light sources which might interfere with the fNIRS-signal by protecting the measured brain region with a light impermeable cap. Moreover, before starting the experiment participants should be informed that strong and abrupt (head)movements during data collection should be avoided. This is essential in order to guarantee appropriate fNIRS data quality and prevent strong (movement) artefacts.

In comparison to a stationary conducted fNIRS experiment, the implementation of mobile fNIRS might be even more challenging, as it implies an adequate preparation of the experimental setting in which the data acquisition takes place. Moreover, given that it is rather difficult to define the occurrence of stimuli in a mobile, naturalistic experiment beforehand, it is necessary to combine mobile fNIRS with other neurophysiological methods such as eye-tracking to control for external, environmental cues. This is also relevant for the data analysis of fNIRS experiments conducted in the field, as it takes significantly more time and effort to analyse the data as the stimuli onsets have to be defined *ex post* and with the help of another neurophysiological methods such as e.g., eye-tracking. Nevertheless, based on our research work and recent research findings (Krampe et al., 2018a,b), it should be evident that the advantages of conducting mobile fNIRS experiment may exceed potential disadvantages.

The third step in this process is the data analysis. Before starting the data analysis, scholars need to define task-specific events based on the *ex-ante* established paradigm or manually by defining the onsets (time a stimulus occurred) and length of the stimulus (time a stimulus was present) for every event respectively. This is essential in order to analyse the data statistically. Similar to other neuroimaging data analysis procedures, for example fMRI, the fNIRS analysis process may be subdivided into several components.

First, scholars need to check the signal quality of every diode and optode previously defined in a topographic map of the cortex (**Figure 2**). Second, irrelevant time series might be truncated in order to exclude time intervals from further consideration, which are not relevant to answer a particular research question. Third, scholars might remove discontinuities and spike artefacts from the data time series, which are clearly and apparently qualified as confounding effects. Thereby, abnormalities that have two or more adjacent channels with t-values over three standard deviations from the group average (Fishburn et al., 2014) or which indicate significantly more spike artefacts might be excluded from further analysis. Fourthly, scholars should apply a high, low or band-pass frequency filter in order to smooth the fNIRS data time series. Thereafter, scholars need to decide which light signal (alternatively raw data) they would like to investigate. As the oxy-Hb signal has been shown to correlate with cerebral blood flow better than the deoxygenated signal (Hoshi et al., 2001), most of the fNIRS data analysis focuses on the oxy-Hb light signal. It should, however, be evident that mobile fNIRS is capable of examining raw data, oxygenated,

[3]https://nirx.net/nirstar-1/

deoxygenated and total haemoglobin concentrations, which is one advantage in comparison to other neuroimaging methods. Thereafter, scholars might convert the raw near-infrared light absorption and attenuation data into oxy-, deoxy- and/or total-haemoglobin concentrations. The most common used algorithm for this progression is the modified Beer-Lambert law (Kocsis et al., 2006; Kopton and Kenning, 2014; Scholkmann et al., 2014), which is integrated in the previously described "NirsLab" toolbox, containing several parameters as described in the data analysis section above.

Once the data have been processed, scholars might analyse the haemodynamic-state time series, as defined before based on the *ex-ante* established paradigm, on within-session and/or within-subject level or across multiple sessions or between-subject level. Thereby, a GLM on individual level will be set up to model neural activity during the experimental task, based on the predefined stationary or mobile paradigm.

Finally, to identify the underlying brain regions involved, statistical results are depicted on a standardised brain to visually locate the neural activation patterns and interpret them. Scholars should be very careful about the localisation and designation of the associated brain regions, encouraging scholars to apply the previously introduced classification map of the PFC.

CONCLUSION

Returning to the research questions—is mobile fNIRS a valid neuroimaging method for "neuro-marketing" and consumer neuroscience?—we suggest, the answer is "yes, in principle but." confirming that mobile fNIRS is in some situations and circumstances an appropriate neuroimaging method able to expand knowledge on several marketing research related issues. Thereby, mobile fNIRS has a good temporal resolution but is restricted in its spatial resolution.

By keeping in mind that there are various mobile fNIRS technologies, which might also be applied in the research field of marketing, recent research demonstrated the usability of smaller, two-channel, portable fNIRS devices and its utility in order to investigate emotional and/or stress processes (Brugnera et al., 2017, 2018; Adorni et al., 2018), indicating the proliferous, ongoing technological progression of mobile fNIRS and its potential for marketing research.

Against this background and based on our research findings, we encourage marketing research to apply mobile fNIRS, following our and already established guidelines (Brouwer et al., 2015; Plassmann et al., 2015), whenever the immobility of another method becomes an issue and when previous research indicates that cortical, near surface brain regions are involved.

AUTHOR CONTRIBUTIONS

CK, as first author, conducted the study, performed the data analysis and wrote the manuscript. NG participated in carrying out the study and performed the data analysis. PK helped the first author in developing the study and participated in writing the manuscript. All authors read and approved the final manuscript.

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The Hazard Perception for the Surrounding Shape of Warning Signs: Evidence From an Event-Related Potentials Study

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Surrounding shape is a very important component of warning signs. Unlike colors, signal words, and pictorials that can directly convey the surface meaning, the surrounding shapes of warning signs convey warning information somewhat obscurely. Most of the researchers who studied this topic investigated the individuals' hazard perception of the surrounding shapes of warning signs by using questionnaires. In addition, the scholars' points about the role of the surrounding shapes are inconsistent. This study, therefore, decided to use Event-Related Potentials (ERP) technology to explore the impact of the shapes on the perception of warning signs to find the evidences of the hazard perception of the shapes from the electrophysiological perspective. Using the Oddball paradigm, we found four components caused by different shapes of warning signs. Specifically, P200 amplitude characterizes the attraction to attention of surrounding shapes in the early automatic perception stage, the N300 components represented the emotional valance and arousal level, the P300 and the LPP connoted uneasy/unsafe information and reflected the inhibition strength on the uneasy/unsafe information. Experimental data indicated that the shape of UPRIGHT TRIANGLE had larger arousal strength and more negative valence than the shape of CIRCLE. People get stronger negative information from the UPRIGHT TRIANGLE shapes than from the CIRCLE. This finding might be helpful for designing the surrounding shapes of warning signs.

Keywords: warning signs, surrounding shapes, Event-Related Potentials (ERP), neural industrial engineering (NeuroIE), neuromanagement

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INTRODUCTION

Visually, it is an effective way to communicate hazard information through warning signs. Hazard information delivered by warning signs are considered necessary in a variety of industries. The basic elements of the warning signs are composed of signal words, colors, surrounding shapes, and pictorial symbols (Young, 1998). It has been found that the surrounding shape was an important factor to affect the perception of hazard information and the reaction time to avoid hazard, specifically, the INVERTED TRIANGLE got higher warning score and made people react faster than did the shape of CIRCLE. The Chinese word "危险(DANGER)" surrounded by INVERTED TRIANGLE shape constituted the most effective warning sign to deliver the hazard information (Wang et al., 2008). The relations between individual's variables (such as sex, age, education, familiarity with warning sign, and risky preference) and the perception of the warning signs were been studied (Rogers et al., 2000). It was revealed that the colorful signs might be more useful than monotone signs or signs with fewer colors for young children (Siu et al., 2015). In addition to the studies on the elements of the warning signs, some researches paid attention to the theory of warning signs. For instance, the communication-human information processing (C-HIP) model of warning signs suggested that there were four stages of information processing before action when people were seeing warning signs. The four stages included attention, comprehension, attitudes and beliefs, and motivation (Wogalter et al., 2005; Shang et al., 2015). By using Event-Related-Potential (ERP) techniques to study this issue, the researchers found that there were only two stages occurred in brain about dealing with the signal words in safety signs. The first stage was an early automatic cognitive process of consciousness for the risk in signal words, represented by P200; the second stage was the late controlled process in which the risk level that the signal words included was evaluated, represented by LPP (Ma et al., 2010).

As a controversial part of a warning sign, the surrounding shapes, unlike signal words and pictorial symbols that can directly convey the meaning of their surface, cannot deliver warning information directly. The warning effect that shapes convey is somewhat vague. So, most of the investigations about surrounding shapes are usually used together with other elements, such as signal words and pictorial symbols. In earlier studies, Michael A. Rodriguez revealed that written labels surrounded by a shape resulted in higher compliance than the labels without surrounding shape, and the color had significant effects only when used combination with shapes. So the surrounding shape is an important component of the warning sign (Rodriguez, 1991). But until now, there is no consistent answer to the question of whether the surrounding shapes can contribute to warning effect. Rui-feng Yu et al. suggested that some shapes may have a strengthening effect for hazard communication, such as INVERTED TRIANGLE and UPRIGHT TRIANGLE, while some others have a weakening effect, such as RECTANGLE (Yu et al., 2004). Michael W. Riley et al. considered that the INVERTED TRIANGLE was the perfect warning indicator among the shapes, whereas the CIRCLE was generally not perceived as a warning shape (Riley et al., 1982). S. David Leonard deemed that the shape or other graphical configurations might help better than color to convey different levels of risk (Leonard, 1999). Contrary to the above points, Brewster demonstrated that surrounding shapes can make the signal word more difficult to read when approached from a certain perspective (Brewster, 1995). Stephen L. Young thought that surrounding shapes made warning signs difficult to read (Young, 1998). Up to now, some studies evaluated the surrounding shapes alone, and some others investigated the surrounding shapes with a variety of elements together, such as warring words, pictorial symbols, and colors. The shapes that have been studied covered UPRIGHT TRIANGLE, INVERTED TRIANGLE, DIAMOND, CIRCLE, and RECTANGLE, etc.

There are some researches aiming at context-free geometric shapes or the outline of a semantically neutral object. In detail, Christine L. Larson et al. had used an Implicit Association Test to examine associations between three shapes (downward- and upward-pointing triangles, circles) and pleasant, unpleasant, and neutral scenes. They found that even very simple context-free geometric shapes have been shown to signal emotion, conveying affect associated with perception of threat or unpleasantness. Where the downward-pointing triangles are quickly classified as unpleasant, the circle is considered pleasant. And they extend the support for the configural hypothesis of affect perception to the domain of implicit cognition (Larson et al., 2012). Moshe Bar et al. compared amygdala response to objects whose semantic meaning is emotionally neutral but with different types of contour by using fMRI, the result was that the amygdala shows significantly more activation for the sharp angled objects compared with their curved counterparts, and experiments had verified that this activation is related to contour type (Bar and Neta, 2007). Indeed, the amygdala has been shown to respond to implicit, non-conscious cues of threat, so that these sharp visual elements can increase the sense of threat and danger (Whalen et al., 1998).

But almost all the previous studies took interview and/or questionnaire to record the subjects' perception of arousal strengthen of the elements of warning signs, and considered these results as the effectiveness of the elements of warning signs (Wang et al., 2008). These approaches are largely influenced by the participants' intuition and daily experience, so that, in fact, it was a result of immunization. In the past, there were only a few studies which used physiological techniques, such as the electroencephalogram (EEG) and ERP, to study the effectiveness (Ma et al., 2010). As we mentioned above, the shapes had not the strong readable meaning as same as the warning words and pictorial symbols had. So far, the effectiveness of the shapes in warning signs were still controversial. This study, therefore, tried to apply ERP to examine the effectiveness of the shapes and the process of perception and cognition of the shapes.

ERP is a kind of electrophysiological techniques which directly measure the subject's perception and cognition process of the stimulus. In most of the ERP experiments about warning signs, participants were asked to estimate the perceived hazard level of a warning sign whenever they saw the sign, and at the same time, their EEG were recorded (Ma et al., 2010). Only a few studies let subjects finish the task of estimation on hazard level and hiding the real purpose of the experiment. This study used an Oddball paradigm in which the subjects had to press a key when the non-warning-sign picture, such as umbrella, was presented, whereas they had no task when the picture of a warning sign was presented, so as to avoid a "relevance-for-task" effect (Carretié et al., 1997b; Yuan et al., 2007).

P200

P200 is an early positive ERP component with a peak latency from 100 to 200 ms, and is considered to be an indicator at the boundary of unconsciousness and consciousness, and it seems to be an attention bias occurring automatically (Huang and Luo, 2006), and to be sensitive to the emotionality of stimuli (Wang et al., 2012). A Previous study had shown that P200 was associated with early detection of threatening stimuli, such as frightful images (Correll et al., 2006). And the enhanced P200 amplitude showed the distribution of attention resources to significant stimuli (Carretié et al., 2001). In implicit emotional task, a frontal P200 was elicited in all conditions, meaning rapid detection of typical stimulus features. A previous study found that the smaller P2 amplitude was observed for the extremely negative (EN) condition than for the moderately negative (MN) and neutral conditions. What is more, the study observed shorter P2 latency for the EN condition than for the MN and neutral conditions, suggesting that people perceived EN things more faster than others (Yuan et al., 2007).

N300

It was suggested that the N300 component of the ERP constituted a useful tool for studying the emotional reactions to visual stimuli, and it was less influenced by cognitive variables than P300. N300 showed larger amplitudes related with the activating positive visual stimuli, especially at parietal sites (Carretié et al., 1997b). So the N300 has been proved in previous studies that it represented an ability to constitute a more suitable component for distinguishing the different affective characteristics of visual stimuli, and its highest amplitude was in response to activating ones (Carretié et al., 1997a).

P300

P300 is a positive ERPs component with a peak latency between 300 and 400 ms after stimuli, and it widely scattered in the brain area with the amplitudes increase from front to back. It is associated with evaluative categorizations, and reflects the cognitive evaluation of stimuli's meaning (Ito et al., 1998; Huang and Luo, 2006), and differentiates emotional or threatening stimuli from neutral stimuli during active evaluation (Correll et al., 2006; Muñoz and Martín-Loeches, 2015). It was found that the P300 elicited by EN stimuli had shorter latencies when comparing with the stimuli in MN and neutral conditions, showing that the meaning of EN stimuli were preferentially analyzed and evaluated, and the P300 amplitude evoked by the EN stimuli was the smallest among the three conditions, and the largest by the neutral stimuli (Yuan et al., 2007). Studies also indicated that posterior P300 is an index of an inhibition of task-irrelevant information, and also represents later conscious categorization, decision-making and premotor response-related activities (Donchin, 1981; Goldstein et al., 2002). The amplitude of P300 may, therefore, reflected the degree that people resisted the irrelevant task (Yuan et al., 2007).

LPP

Late positive potential (LPP) is an ERP component maximal over central-parietal regions occurring between 300 and 700 ms after stimuli onset, and is modulated by the emotional intensity of a stimulus (Brown et al., 2012). It was proved that the hazard level that the warning words contained was represented by LPP compoment (Ma et al., 2010).

Based on foregoing studies on warning signs and ERP components, we speculate that the individual's perception and cognitive process of different surrounding shapes of the warning signs are different. And the differences can be reflected by the ERPs components (P200, N300, P300, and LPP). We suppose that the different shapes of warning signs might evoke the components of P200, N300, P300, and LPP. In particular, the P200 amplitude characterizes the attraction to attention of surrounding shapes in the early automatic perception stage, the N300 component represents the emotional valance and arousal level, the P300 connotes uneasy/unsafe information and reflects the degree that people resisted the irrelevant task, and the LPP reflects the emotional intensity of a stimulus. According to the inquiry from small-scale questionnaire, we guess that it is more effective for UPRIGHT TRIANGLE to be the surrounding shape of the warning signs to convey hazard information than for CIRCLE.

METHODS

Participants

A total of 20 Chinese students from Zhejiang University enrolled in this experiment, data from one participant were excluded because of excessive recording artifacts. The remaining 19 participants ranged from 20 to 27 years old (mean = 23.79, *SD* = 2.04). All reported normal or corrected-to-normal vision and had no history of current or past neurological or psychiatric illness. Informed consent was obtained from all participants, and this study was approved by the Ethics Board of Zhejiang University Neuromanagement Laboratory. At the end of each experiment, the participant got a fee of ¥ 40. And finally, valid data of 19 subjects were obtained for analysis.

Experimental Materials

In this study, an Oddball paradigm was used, and the target stimuli were 7 kinds of tables and chairs. Each of target stimuli was presented 3 times, so there were total 21 trials for target stimuli. Non-target stimuli included two kinds of shapes (CIRCLE vs. UPRIGHT TRIANGLE) with 14 kinds of pictorial symbols inside the surrounding shapes. Each non-target stimulus appeared also 3 times, so each condition (CIRCLE or UPRIGHT TRIANGLE condition) contained 42 trials, and there were total 84 trials for non-target stimuli. The shapes were made of white background with a thin, inked black line border. The pictorial symbols inside the signs were selected from neutral indicative warning signs, such as the direction of exit, to exclude other influence, and the color of the surrounding shapes was black too. All the stimuli materials were processed by Photoshop software to keep their quality, aspect, gray scale, and pixel the same (see **Figure 1** as an example, see the **Supplementary Figure 1** for details). All stimuli were presented at random.

Experimental Procedure

The participants sat comfortably in a dimly lit, sound-attenuated and electrically shielded room, and the keypad was fixed on the chair. The stimuli were presented centrally on a computer screen at a distance of 100 cm away from the subjects. Firstly, the experimenter introduced the instruction and conducted a brief practice exercise. The experiment was about 5 min, meanwhile, the participants' EEG were recorded throughout the experiment. The experiment was consisted of 105 trials. At the beginning

FIGURE 1 | Pictures are stimuli showed to participants. For examples, **(A)** shows the non-target stimuli for neutral indicative warning signs with two conditions (UPRIGHT TRIANGLE vs. CIRCLE) and **(B)** shows the target stimulus for chair.

of each trial, a fixation appeared as a cue for 500 ms, after a blank screen presented for a duration varying randomly between 400 and 600 ms, followed by the stimuli materials which was presented at the center of screen for 1,000 ms. Participants were asked to respond as quickly as possible with the thumb on the "1" button on the keyboard when the target stimuli occurred. The responding hand was counterbalanced across participants. At the end of a trial, an empty screen was presented about 300 ms (see **Figure 2**).

When the participants complete the experiment, they were asked a question: Which surrounding shapes, CIRCLE or UPRIGHT TRIANGLE, of the warning signs do you think is more vigilantly?

ERP Data Acquisition

EEG was continuously recorded (band-pass 0.05–100 Hz, sampling rate 500 Hz) with the Neuroscan Synamp2 Amplifier (Scan 4.3.1; Neurosoft Labs, Inc., Sterling, Virginia, USA). And using an electrode cap with 64 Ag/AgCl electrodes, according to the international standard 10–20 system. The left mastoid served as on-line reference. EEGs were off-line re-referenced to the average of the left and the right mastoids. The electrode on the cephalic location was applied as ground. Vertical and horizontal electrooculogram (EOG) were recorded with two pairs of electrodes, a pair of electrodes placed between the two sides of the eye (horizontal EOG) and the other placed upper and lower left eye 10 mm. All EEG electrode impedances were maintained below 5 kΩ.

ERP Data Analysis

In the off-line analysis, the EEGs under different surrounding shapes were averaged. Ocular artifacts were corrected with an eye-movement correction algorithm provided by Neuroscan 4.3 software. The ERPs were digitally filtered using a low pass filter at 30 Hz (24 dB/octave) and corrected to the baseline. EEG recordings were extracted from −200 to 800 ms and time-locked to the onset of stimulus, and the whole epoch was baseline-corrected by the 200 ms interval prior to stimulus onset and peak-to-peak deflection exceeding $\pm$ 80 μV were excluded. More than 30 sweeps for each condition remained.

The mean amplitude in the time window of 170–220 ms after the stimuli onset was calculated for P200, the time window of 285–325 ms for N300, the time window of 220–300 ms for P300, and the time window of 450–700 ms for LPP. In order to analyze the effects of these components, we selected the five electrode points (F1, F3, FZ, F2, and F4) in the frontal area to analyze P200 and N300. P300 was analyzed by selecting six electrode points (C3, CZ, C4, CP3, CPZ, and CP4), and nine electrodes (C3, CZ, C4, CP3, CPZ, CP4, P3, PZ, and P4) in the central and parietal area were selected for LPP.

In this experiment, repeated measurements were used to measure variance analysis with two factors: Surrounding Shapes (CIRCLE vs. UPRIGHT TRIANGLE) and the Electrodes for each of the four components.

RESULTS

Behavioral Results

According to statistics, only one participant considered the shape of CIRCLE was more alert than the UPRIGHT TRIANGLE. Others had the opposite view.

Event-Related Potentials Results

P200

The 2 (Surrounding Shape: CIRCLE vs. UPRIGHT TRIANGLE) $\times$ 5 (Electrode: F1, F3, FZ, F2, and F4) repeated measure ANOVA on P200 revealed a significant main effect for the Surrounding Shape [$F_{(1,18)} = 6.616$, $p < 0.05$]. The P200 amplitude elicited by UPRIGHT TRIANGLE (mean = 0.878 μV) was significantly smaller than that by CIRCLE (mean = 2.029 μV). But there was no significant difference between the electrodes. And the interaction between the Surrounding Shape and the Electrode did not show a significant difference (see **Figure 3**).

N300

As to N300, the 2 (Surrounding Shape: CIRCLE vs. UPRIGHT TRIANGLE) $\times$ 5 (Electrodes) repeated measure ANOVA revealed a significant main effect for the Surrounding Shape [$F_{(1,18)} = 9.630$, p <0.05]. And there was a greater N300 amplitude in the condition of UPRIGHT TRIANGLE (mean = 0.643 μV) when compared to the condition of CIRCLE (mean = 1.855 μV). But no significant differences between the electrodes were found. The interaction between the Surrounding Shape and the Electrode did not show a significant difference (see **Figure 3**).

P300

The 2 (Surrounding Shape: CIRCLE vs. UPRIGHT TRIANGLE) $\times$ 6 (Electrode) repeated measure ANOVA on P300 revealed a significant main effect for the Surrounding Shape [$F_{(1,18)} = 14.588$, $p < 0.005$]. A remarkably larger P300 was found for the shape of CIRCLE (mean = 5.363 μV) when compared to the shape of UPRIGHT TRIANGLE (mean = 4.185 μV). And there was also a significant difference between the electrodes [$F_{(5,90)} = 6.353$, $p < 0.005$]. But the interaction between the Surrounding Shape and the Electrode did not show a significant difference (see **Figure 4**).

LPP

The 2 (Surrounding Shape: CIRCLE vs. UPRIRHT TRIANGLE) $\times$ 9 (Electrode) repeated measure ANOVA on LPP showed a significant main effect for the Surrounding Shape [$F_{(1,18)}$ =

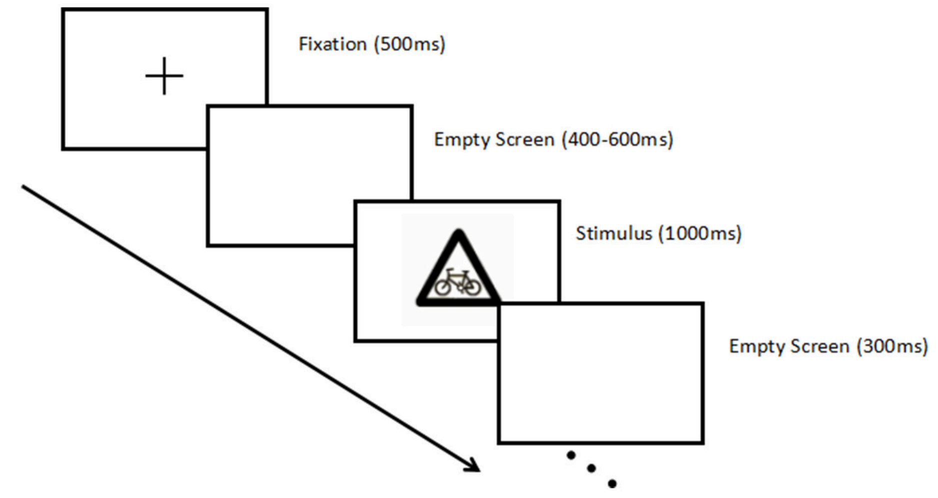

FIGURE 2 | Illustration of the stimulus paradigm applied.

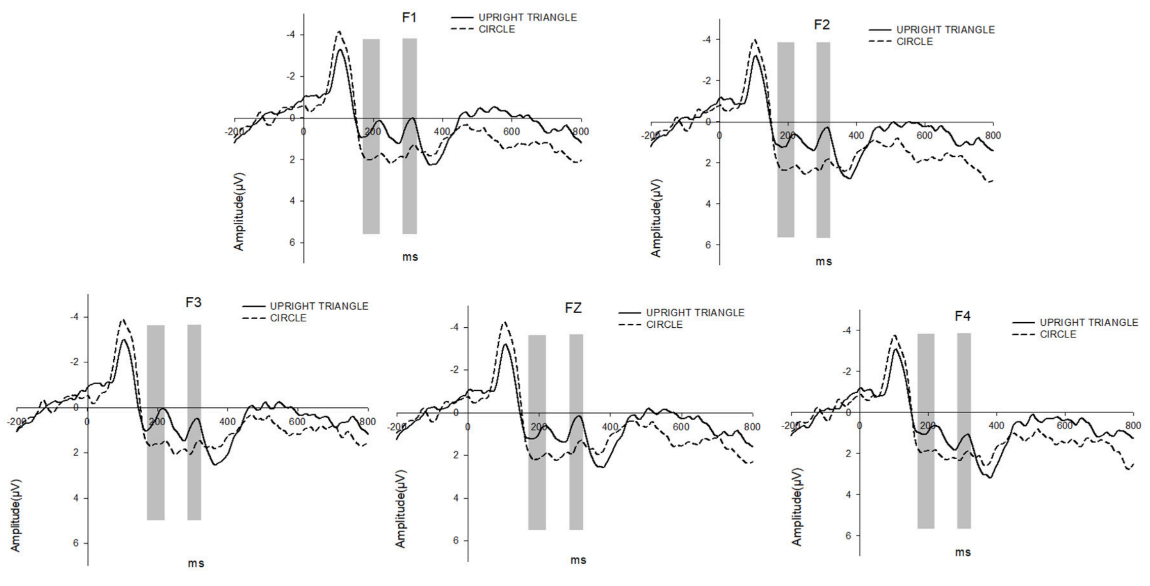

FIGURE 3 | c P200 and N300 were elicited by UPRIGHT TRIANGLE condition (solid line) and CIRCLE condition (dashed line), respectively. The time window for P200 is 170–220 ms and that for N300 is 285–325 ms.

9.947, p= 0.005]. Comparing to the shape of CIRCLE (mean = 3.398 μV), UPRIGHT TRIANGLE (mean = 2.110 μV) showed an evident smaller LPP amplitude. But there no other significant effects could be demonstrated about the Electrode and the interaction between the Surrounding Shape and the Electrode (see **Figure 5**).

DISCUSSION

In previous studies on warning sign, the viewpoints about the effectiveness of the surrounding shapes were most divisive (Riley et al., 1982; Leonard, 1999; Yu et al., 2004). Stephen L. Young argued that surrounding shapes made warning signs difficult to read, and its profits might be less than its defects (Young, 1998), while Yu et al. (2004) as well as Riley et al. (1982), by using the behavior experiments or questionnaire, gave a clear order of the warning levels that were delivered by different surrounding shapes. The results of the current study, from the perspective of the cognitive neuroscience, provided evidence to prove that ERP components related to attention (represented by P200), valence and arousal (represented by N300) are affected by the UPRIGHT TRIANGLE border, and more uneasy/unsafe information which was inhibited more strongly at the cognitive level (represented by P300 and LPP) when compared with CIRCLE.

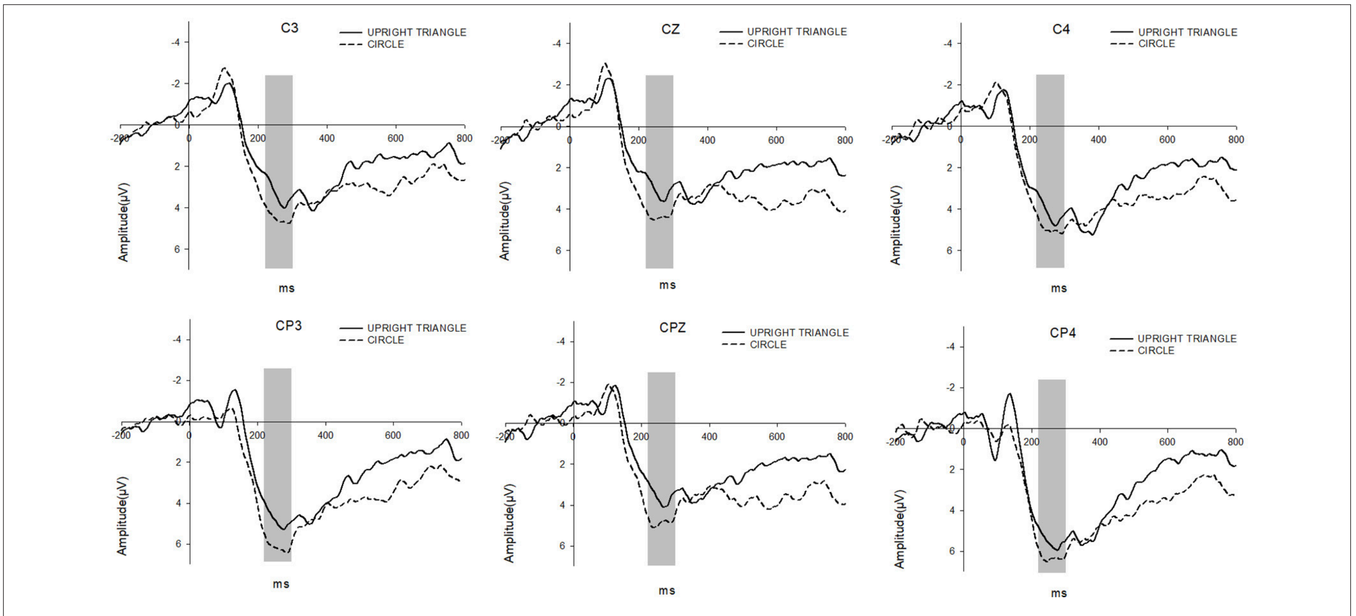

FIGURE 4 | P300 were elicited by UPRIGHT TRIANGLE condition (solid line) and CIRCLE condition (dashed line), respectively. The time window for P300 is 220–300 ms.

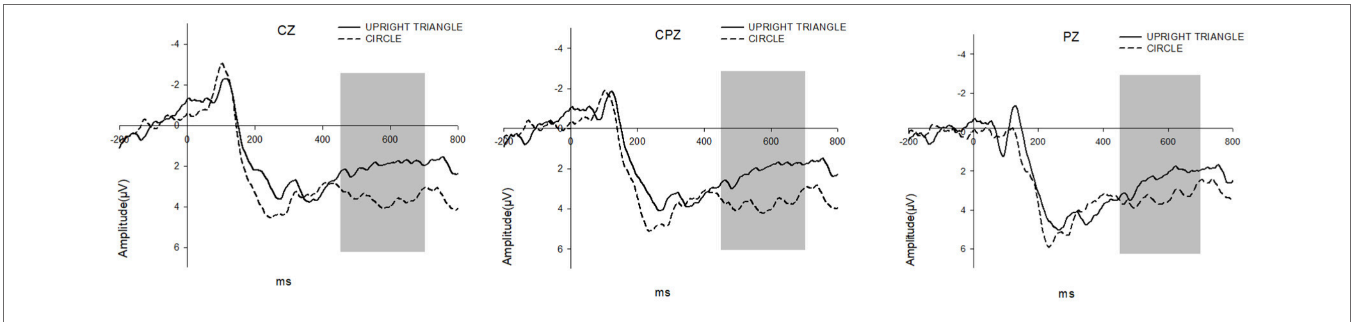

FIGURE 5 | LPP were elicited by UPRIGHT TRIANGLE condition (solid line) and CIRCLE condition (dashed line), respectively. The time window for LPP is 450–700 ms.

By using ERP with high temporal resolution, we found four ERP components might be considered as the physiological indicators of the perceived and cognitive processes after seeing the warning signs. In details, firstly, according to the previous study (Yuan et al., 2007) which showed the frontal P200 activation was an automatic and rapid detection to the threatening content, and more attention resource was recruited in this process when compared with neutral condition, our result of P200 suggested that the UPRIGHT TRIANGLE border was detected automatically and more quickly when compared to the CIRCLE border. Besides, the current study provided direct evidence to support above suggestion: the P200 latency for UPRIGHT TRIANGLE border was significantly shorter than for CIRCLE border, meaning that the response to UPRIGHT TRIAANGL border was faster than to CIRCLE. This electrophysiological founding supported the previous behavioral research which found that people reaction time to TRIANGLE was less than to CIRCLE (Wang et al., 2008).

Secondly, the N300 was an emotion-sensitive component. Unlike P300 which was mainly evoked by the cognitive processing, the N300 was less influenced by cognitive variables (Carretié et al., 1997b). L. Carretié and colleagues in their studies (Carretié et al., 1997a,b) used a distracting task (to focus on the "correspondence" or different themes of stimuli) to disguise the real aim of the experiments to avoid the "relevance-for-task effect," and found that the "activating and repulsive" stimuli (such as human remains) elicited more negative N300 in frontal and parietal regions when compared to the "activating and attractive" stimuli. The current study which also adopted the distracting task (to focus on the target stimuli, such as tables and chairs) found that the UPRIGHT TRIANGLE border elicited larger N300 amplitude in frontal region than did the CIRCLE border, whose logic was very similar to studies (Carretié et al., 1997a,b), suggesting that the UPRIGHT TRIANGLE border delivered more uncomfortable/uneasy/unsafe felling to subjects when compared with the CIRCLE border, i.e., the UPRIGHT

TRIANGLE has higher negative valence than the border of CIRLCLE has.

Wei et al. (2011) compared the differences in neural response to negative or positive words between the group in which individuals had traumatic experience in earthquake and the group having no the experience. They found that more negative N300 effect for negative words than for positive ones in the earthquake group, whereas no this effect was found in the control group (having no experience in earthquake). The result showed that more negative N300 may reflect heightened emotional arousal to negative information as well as the processing of negative-relevant information. Similarly, our results that the more negative N300 effect was found for UPRIGHT TRIANGLE border might reveal that the border of UPRIGHT TRIANGLE had higher arousal strength and more negative valence to subjects, suggested that the UPRIGHT TRIANGLE was more suitable than CIRCLE to serve as the surrounding shape of the warning sign to deliver hazard information in order to affect the individuals' performance.

Thirdly, P300 represented many cognitive processes in different experimental processes or different tasks. One kind of the cognitive processes is the process of the cognitive evaluation of stimuli's meaning (Ito et al., 1998; Huang and Luo, 2006).

In the implicit-evaluation experiment, the process of evaluation on the non-target stimuli was implicit and automatic. The participant would inhibit the target-irrelevant information, in order to respond to the target stimuli more accurately. Especially, the inhibition of the negative valence information would be stronger. It has been vastly demonstrated that posterior P300 was an index of the inhibition process of target-irrelevant information (Campanella et al., 2002; Goldstein et al., 2002). The smaller amplitude of P300 represented stronger inhibition of the negative valence information (Yuan et al., 2007).

The result that the UPRIGHT TRIANGLE stimuli elicited smaller P300 than did the CIRCLE stimuli suggested that the UPRIGHT TRIANGLE evoked more uncomfortable feeling of the subjects than did the CIRCLE shape. The reason might be that the sharp angle of the TRIANGLE brings people an uneasy feeling and further an unsafe perception. In other words, the UPRIGHT TRIANGLE border delivered more hazard information to subjects than did the CIRCLE border.

Fourthly, LPP is another ERP component which may be elicited by emotional stimuli (Brown et al., 2012). In many cases, LPP is considered as a continuation of the evaluation process represented by P300. The amplitude of LPP is recognized as a reflection of the familiarity with the stimuli, such as own name (Symons and Johnson, 1997), or other self-relevant information (Miyakoshi et al., 2007). The more familiar with the stimulus image, the larger of the LPP is. Our findings were consistent with the previous studies (Symons and Johnson, 1997; Miyakoshi et al., 2007; Zhao et al., 2009). The CIRCLE shape is so common in daily life, such as wheels, cups, buckets, and dishes, that people are too familiar with it to cause alarm. While the UPRIGHT TRIANGLE shape is rarely seen in ordinary life. Once it appears, it is easy to attract attention, therefore, the warning sign with the UPRIGHT TRIANGLE border can easily convey the hazard information.

CONCLUSION

The surrounding shape of UPRIGHT TRIANGLE had a greater attraction to attention (represented by P200), more negative valence and higher arousal level (represented by N300), and more uncomfortable/uneasy/unsafe information which was inhibited more strongly at the cognitive level (represented by P300 and LPP) when compared to the shape of CIRCLE, resulting in that the surrounding shape of UPRIGHT TRIANGLE was more suitable to use to deliver hazard information when designing a warning sign.

We believe that different borders have different warning effects and can be measured by electrophysiological indicators. At present, we are also conducting some extended research. The experiments we are doing have explored the interaction between multiple sign elements. Also for future research, we are going to study the comparison of various shapes, rather than simple triangles and circles. What's more, it's an interesting idea to assess the effect of different surrounding shapes on ERPs at a subliminal level, which could disentangle implicit and explicit effects.

ETHICS STATEMENT

This study was carried out in accordance with the recommendations from the ethics committee of Neuromanagement Lab, Zhejiang University. All subjects gave a written informed consent according to the Declaration of Helsinki. All participants had normal or corrected-to-normal vision. None of them reported any history of psychiatric or neurological disorders.

AUTHOR CONTRIBUTIONS

QM and ZX conceived and designed the experiments. XB and GP performed the experiment. XB and GP analyzed the data. QM, XB, and GP wrote and refined the article.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fnins.2018.00824/full#supplementary-material

Supplementary Figure 1 | Pictures are stimuli showed to participants, including non-target stimuli and target stimuli.

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Neural Correlates of Preference: A Transmodal Validation Study

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Liking is one of the most important psychological processes associated with the reward system, being involved in affective processing and pleasure/displeasure encoding. Currently, there is no consensus regarding the combination of physiological indicators which best predict liking, especially when applied to dynamic stimuli such as videos. There is a lack of a standard methodology to assess likeability over time and therefore in assessing narrative and semantic aspects of the stimulus. We developed a time-dependent method to evaluate the physiological correlates of likeability for three different thematic categories, namely: adventure (AV), comedy (CM), and nature landscape (LS). Twenty-eight healthy adults with ages ranging from 18 to 35 years (average: 23.85 years) were enrolled in the study. The participants were asked to provide likeability ratings for videos as they watched them, using a response box. Three 60-s videos were presented, one for each category, in randomized order while the participant's physiological data [electroencephalogram (EEG), electrocardiogram (ECG) and eye tracking (ET)] was recorded. The comedy video (CM) presented the smallest minimum accumulated normalized rating (ANR; $p = 0.013$) and the LS video presented the highest maximum ANR ($p = 0.039$). The LS video presented the longest time for first response ($p < 0.001$) and the AV video presented the shortest time for maximum response ($p = 0.016$). The LS video had the highest mean likeability rating with 1.43 ± 2.31 points; and the CM video had the lowest with 0.57 ± 1.77. Multiple linear regression models were created to predict the likeability of each video using the following physiological indicators; AV: power in beta band at C4 and P4 ($p = 0.004$, adj. $R^2 = 0.301$); CM: alpha power in Fp2 ($p = 0.001$, adj. $R^2 = 0.326$) and LS: alpha power in P4, F8, and Fp2; beta power in C4 and P4 and pupil size, ($p = 0.002$, adj. $R^2 = 0.489$). Despite its limitations (e.g., using one 1-min video per category) our findings suggest that there is a considerable difference in the psychophysiological correlates of stimuli with different contextual properties and that the use of time-dependent methods to assess videos should be considered as best practices.

Keywords: liking, affective reactions, time-dependent measurement, EEG, ECG, eye tracking, neurocinematics

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INTRODUCTION

The brain reward system is composed of three subsystems involving learning, emotional and motivational processing, according to Berridge and collaborators. Respectively, these components are responsible for reward learning, liking and wanting (Berridge, 2004; Berridge et al., 2009; Berridge and Kringelbach, 2013, 2015). All of them have explicit and implicit constituents and a vast number of studies have involved efforts to build bridges between the two, using purely neuroscientific or mixed strategies, which often involve fMRI (Silberstein and Nield, 2008; Kühn and Gallinat, 2012), electroencephalogram (EEG; Han et al., 2017), peripheral electrophysiology (Sánchez-Navarro et al., 2008) and eye tracking (ET; R.-Tavakoli et al., 2015).

Liking is recognized as one of the most important psychological processes associated with the reward system. It is associated with affective processing and pleasure/displeasure encoding, which provides feedback that guides the interaction with every stimulus which one encounters (Steiner et al., 2001; Berridge et al., 2009; Kringelbach and Berridge, 2010; Smith et al., 2011; Berridge and Kringelbach, 2013, 2015). The declarative component of liking can be measured through the explicit response of the subject; however, the non-declarative component requires a more specific approach, such as the psychophysiological evaluation of affective reactions or behavioral analysis.

Affective reactions can be described in terms of two fundamental dimensions: valence (pleasure/displeasure) and arousal (activation/inhibition; Russell, 1980, 2003; Gerber et al., 2008). These dimensions tend to relate to each other in "V" shape fashion; high arousal and positive valence encode high likeability, whereas high arousal associated with a negative valence leads to unlikeable experiences (Kuppens et al., 2013). Despite the large body of research on valence-arousal approach and its physiological correlates, the current literature is focused on a global assessment of the emotional phenomena, employing measures to rate the stimulus as a whole, such as the Self-Assessment Manikin (Bradley and Lang, 1994) or through visual analog scales.

While being appropriate for assessing static stimuli such as images, a global assessment may not be the best option to assess complex stimuli which change dynamically over time, such as videos. Audiovisual stimuli comprise the current mainstream form of media communication and perhaps the best resource for inducing affective reactions in a controlled and easily reproducible environment. Videos have better ecological validity than images and sounds, as they can embrace more comprehensive narratives over time, and are therefore closer to a real-life experience.

Time-dependent measures have been used to evaluate dynamic changes of perception in sensory evaluation for more than 80 years, starting with studies by Holway and Hurvich (1937) on taste perception. Time-dependent methods are a set of descriptive analysis techniques that allow the monitoring of changes in the temporal sensory profile of a stimulus. As a descriptive technique, it usually provides detailed, precise, reliable and objective information regarding the stimulus sensorial attributes. Unlike non-time dependent measures, which provide a global sensory profile of the stimulus, time-dependent measures are focused on capturing dynamic changes in one or more attributes, providing insightful data when detailed time information is needed (Hort et al., 2017). These methods have been consistently applied to assess affective responses such as liking for certain foods in studies since the 1990s (Taylor and Pangborn, 1990; Sudre et al., 2012; Jager et al., 2014; Thomas et al., 2015).

Surprisingly, very few authors have employed time-dependent measures, despite them being well established, to assess affective response induced by videos. In a recent systematic review conducted by our team on affective psychophysiological responses to videos stimuli (submitted article), we noted that only one study (Golland et al., 2014) employed time-dependent measures to assess the declarative components of affective reaction whilst investigating their psychophysiological correlates [i.e., EEG, electrocardiogram (ECG) and ET]. This is worth noting, as there is a known methodological limitation in evaluating the affective impact of video narratives in affective reactions by requiring subjects to recall and the experience they had throughout their duration, due to the so-called Primacy-Recency Effect in short-term memory (Henson, 1998), which is the tendency to remember information presented at the beginning and at the end of a series of events, hence overestimating these moments when declaring the likeability of a video.

Our review shows that most studies tend to look for general psychophysiological patterns, capable of distinguishing pleasant and unpleasant stimuli, with little relation to the contextual aspects of the stimuli. For example, it appears as if certain brainwaves and patterns of activation of the autonomous system have intrinsic value to the subject, as if they translated the occurrence of specific computations in the domain of pleasantness. In contrast to this, two very different experiences, such as watching a horror movie and taking part in a meditation session, may be rated and experienced as equally pleasant, in which the physiological correlates of each experience are expected to be extremely different, aligned with the phenomenological states that trigger the reaction. Feeling relaxed in a horror movie should indicate ineffectiveness, not the opposite, as a generalist approach to these correlates would in fact imply.

Considering that most physiological indicators of affective reactions induced by videos are established using non-time-dependent assessment methods as reference and that affect detection models tend to be more accurate while employing multimodal physiological evaluations (D'Mello and Kory, 2015), the most appropriate combination of physiological indicators to describe the neurobiological correlates of subjective liking using time-dependent measurements are still to be determined or at least further understood.

In light of those issues, the present article, a proof-of-concept study employing a time-dependent method to evaluate its associations to physiological measures, namely EEG, ECG and ET, illustrates how these indicators can be used to predict likeability in three categories of videos: adventure, comedy and observational (videos of nature landscapes).

MATERIALS AND METHODS

Participants

This study involved healthy adults, aged 20–35 years old, with no history of neurological, psychiatric or cardiological diseases. To diminish socioeconomic biases, it was established that all participants were from socioeconomic classes A and B (middle class and above).

The following were included as exclusion criteria: individuals with scores higher than 7 on the SRQ-20, a self-evaluation psychiatric screening questionnaire (Mari and Williams, 1986), morbid obesity, strabismus, having slept fewer than 5 h the night before, chronic use of psychoactive drugs, or having used illegal drugs at least 3 days before the experiment. Thirty-five healthy adults were contacted for the first assessment, and 28 (18 males, mean age 23.85 years) were included on the study. Two participants had slept fewer than 5 h the night before the experiment and three individuals scored more than 7 points on the SRQ-20 questionnaire. Participants were recruited from the University of São Paulo (USP), through announcements made after classes at the university.

Materials

Stimuli Selection and Presentation

Three movies, one from each thematic category, adventure (AV), comedy (CM) and nature landscape (LS), were selected from the Internet, following these selection criteria: (a) creative commons license or any license that allowed editing and reproducing for non-commercial purposes; (b) absence of verbal content; (c) at least 60 s of duration; and (d) 720p quality or higher. The selected videos were "Goliath Roller Coaster 4K POV Walibi Holland" (AV), "Centraal Beheer TVC 70–Acupuncture" (CM) and "Inukshuks under the stars" (LS).

Videos were edited so that they were all the same size and duration[1]. All videos were presented once to each participant in a pseudo-random order. Participants sat 60 cm from the screen and the stimuli were presented on a 15.1-inch LCD display with 1366 × 768 pixel resolution and 60 Hz refresh rate. The stimulus presentation software utilized was Tobii Studio 3.2.

Physiological Measures

Eye movements and pupillometry were recorded using Tobii X2–60 fixed ET, a binocular video-based eye tracker with 60 Hz sample rate. EEG and ECG recordings were made using g.tec gUSBAmp 3.0 from g.tec medical engineering, an FDA and CE certificated amplifier with 24 bits resolution and 16 channels. Electrophysiological data was collected at a 256 Hz sample rate. Twelve channels were used for EEG recordings and two channels for ECG recordings. EEG was recorded with g. SAHARA active system of dry electrodes and ECG was recorded using AgCl passive gel electrodes. EEG electrode positioning was based on the study by Yılmaz et al. (2014) and followed the international 10–20 system: Fp1, Fp2, F1, F2, F7, F8, C3, C4, P3, P4, O1, O2, with the reference positioned on the left mastoid and ground on the right mastoid. ECG followed bipolar positioning with the first active electrode above the right pectoralis major muscle, near the middle of the clavicle and the second electrode was positioned on the left superior portion of the abdomen, near the 7th rib. Reference was positioned symmetrically to the first active electrode, on the left chest and ground was positioned over the trapezius muscle. The limit of the impedance level for data collection was 5 kOhms or less.

Likeability Assessment

Likeability rating was assessed through an Arduino-based response box, with a rotating potentiometer attached to an encoder. Participants were instructed to rotate the potentiometer clockwise to increase the likeability rating or counterclockwise to decrease it, according to their experiences during the video. This device has small ticks, which provide tactile feedback to the participant while rotating it. The reason for using a potentiometer instead of a more conventional approach, like a slider or some rating button models, is that this piece can be rotated infinitely, which allows participants to rate without being constrained by upper or lower limits. A light sensor connected to the monitor was used to synchronize the stimulus presentation, physiological, and likeability data collection.

Procedures

Experiments were conducted in a quiet, dimly lit room. Demographic data, socioeconomic data, education level, laterality, gaze dominance, hours of sleep, use of psychoactive drugs and history of psychiatric, neurological or cardiac diseases were all collected upon arrival. The SRQ-20 questionnaire was also filled out at this moment. Subsequently, participants were asked to sit in front of the monitor and the sensors were attached. After calibration and signal quality assessment, the baseline was recorded and the experiment was set to begin.

An instruction screen was presented telling the participant to rotate the potentiometer to indicate his liking of the videos as he watched them. He was told to the potentiometer clockwise to indicate that he liked the video and counterclockwise to indicate the opposite. In this sense, the more the participants rotated the potentiometer towards a direction, the more intense the corresponding experience (liking or disliking). Participants were also instructed to avoid moving or blinking excessively during the video presentations.

After being certain that each participant understood the instructions, the researcher left the room and the experiment started; a wireless doorbell was provided to call the researcher after the experiment was finished or in case of an issue. A 15-s resting interval was added between each video, to allow the participant to recover emotional homeostasis, avoiding carryover effects from one video to the next.

Data Processing—Subjective Liking

Subjective liking was processed in three complementary analyses: accumulated normalized rating (ANR), sample percentage of response and moving rating sum. The purpose of the ANR

[1]The edited versions of the videos can be found at http://bit.ly/video_FHN

was to highlight likeability trends over time. It was calculated by accumulating given ratings over time (for example, if the participant gave a +1 rating, by turning the potentiometer clockwise, in the second and third samples, and a −1 rating, by turning the potentiometer counterclockwise, in the fourth sample, the rating in the first five samples would be accumulated as follows: 0, 1, 1, 2, 1, 1). This procedure was done in the whole interval and z-scores for all samples for each individual were then calculated; this approach is especially sensitive to the narrative aspects of the video, capturing accumulated variability over time.

The purpose of the sample percentage of response was to create a manipulation test for the method, by assessing whether the participants presented similar response patterns to the stimuli over time, therefore evaluating its performance to assess group trends and providing validity measures for the method. It was calculated by dividing the data into 50% overlapped epochs of 1,000 ms (steps of 500 ms, therefore overlapping 50% of the previous time window, making a total of 90 epochs) and determining the percentage of the sample which presented responses in each epoch, regardless of valence (for example, the sample size was 28, so if 14 participants responded at least one time, during 10 s to 11 s interval, the sample percentage of response for this epoch was 50%. This procedure was repeated for all epochs).

The purpose of the moving rating sum was to assess granular likeability changes over time, highlighting the moments when the stimulus was most relevant. It was calculated by totaling the number of responses in 50% overlapped epochs of 500 ms, comprising 238 epochs. Each epoch was considered independently and each response that indicated liking (rotating clockwise) was coded as +1 and each response that indicated disliking (rotating counterclockwise) was coded as −1 (for example, if a participant rotated the potentiometer four times in 500 ms, rating +1, +1, +1 and −1, the final rating for this epoch would be +2. This procedure was repeated for all epochs). By these means, it was possible to determine the moments of maximum and minimum likeability of each video (i.e., the most and the least liked moments of the video), which were used for subsequent physiological pattern comparison and the regression analysis. The purpose and processing methods for each indicator is summarized in **Figure 1**.

Data Processing—Physiological Measures

Electrophysiological signals were filtered offline using finite impulse response bandpass filters (EEG 2–40 Hz and ECG 2–100 Hz) and a notch filter (60 Hz). Blinks and other eye movements were removed using independent component analysis and noisy channels were interpolated using spherical interpolation. Finally, the signal was visually inspected and sections with artifacts were removed. EEG data preprocessing was made using EEGLAB 14.1 (Delorme and Makeig, 2004).

After data preprocessing, the spectral power of each EEG channel in each sample of the 1.5 s preceding the moments

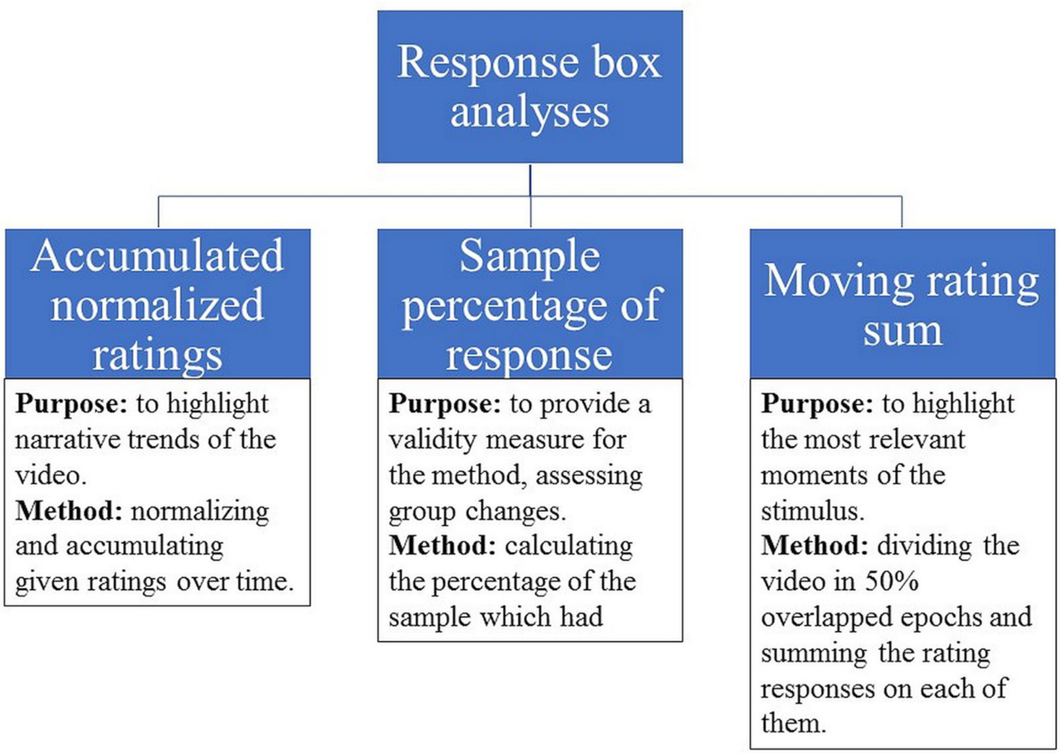

FIGURE 1 | Likeability indicators processing summary.

FIGURE 2 | Physiological data processing and analysis.

of maximum and minimum liking rating was calculated using wavelets transformation. The established frequency bands were: delta (2–4 Hz), theta (4–8 Hz), alpha (8–15 Hz), beta (15–30 Hz) and gamma (30–40 Hz). In order to calculate the mean power in each frequency band, the frequency vector was divided into 0.5 Hz bins and the average values within the frequency intervals were calculated; these procedures were made using Fieldtrip (Oostenveld et al., 2011). The selection of EEG variables to be included in the analysis was done using data of an aforementioned systematic review conducted by our group (submitted) on the psychophysiological correlates of affective reactions induced by videos; namely theta in the left frontal (Fp1, F1 and F7), right parietal (P4) and occipital regions (O1 and O2), alpha in the right frontal (Fp2, F2 and F8) and right parietal (P4), beta in the right frontal (Fp2, F2 and F8), right central (C4), parietal (P3 and P4) and left occipital region (O1) and gamma in the right frontal region (Fp2, F2 and F8).

Phasic cardiac response (PCR) in the 5 s preceding the moments of maximum and minimum liking ratings were calculated using Kardia, a Matlab-based toolbox for cardiologic data processing and analysis (Perakakis et al., 2010). To determine the PCR, the cardiac frequency was calculated on epochs of 200 ms and the data points were interpolated using cubic spline, as suggested by Guimarães and Santos (1998).

Pupil size was determined with Tobi Studio 3.2; this software automatically corrects pupil size according to the distance from the screen. Blinks and missing data were interpolated using Matlab 2015 cubic spline function. The mean pupil size in the 2 s preceding the moments of maximum and minimum liking rating was calculated and used for further analysis, as shown below.

Statistical Analysis

The main objective of this exploratory, proof-of-concept, correlational study was to illustrate the use of a time-dependent approach to assess subjective liking and its physiological correlates to create predictive models. In this sense, the focus of the analysis of subjective liking measures is to highlight the differences between videos and the focus of the physiological univariate analysis was investigating the differences between the moments preceding the maximum and minimum likeability ratings (**Supplementary Material**), which were used in the regression analysis, as described in **Figure 2**. These comparisons were made using Friedman tests with *post hoc* Wilcoxon tests. In addition, these tests were performed for every epoch in order to provide a control measure and descriptive statistics were provided.

A multivariate linear regression model was created for each video, to predict the difference between the maximum and minimum likeability ratings, using as predictors the maximum differences on each physiological indicator in the moments prior to these epochs. Only indicators whose maximum differences were statistically significant at the univariate analysis (displayed in the **Supplementary Material**) were included in the regression analysis. In this sense, the AV video model included cardiac frequency and power in the following sites and frequency bands: theta in Fp1, F1 and O2; alpha in Fp2 and F2; beta in Fp2, F8, F2, C4, P3, P4, O1; and gamma in Fp2, F8, and F2. The CM video model included cardiac frequency, pupil size and power in the following sites and frequency bands: theta in Fp1, F7, F1 and O2; alpha in F1, Fp2, F8 and F2; beta in Fp2, F2, C4, P3, P4, O1; and gamma in Fp2, F8 and F2. The LS video model included, pupil size and power in the following sites and frequency bands: theta in F7, F1, P4 and O2; alpha in P4, Fp2 and F8; beta in Fp2, F8, F2, C4, P3, P4, O1; and gamma in Fp2, F8 and F2. All variables were normalized prior to the model creation and, due to a large number of variables and the sample size, we used a backward stepwise regression method.

The significance level for all tests was established at 95%. Friedman and Wilcoxon's tests were conducted with Matlab Statistics and Machine Learning Toolbox and the Statistics Package for Social Sciences 21 was used for the linear regression model.

RESULTS

Subjective Liking

Accumulated Normalized Ratings

Significant differences were observed in minimum (p = 0.013) and maximum ratings (p = 0.049). *Post hoc* tests showed that CM video minimum rating is significantly lower than AV video minimum rating (p = 0.04) while no significant differences were found in the pairwise comparison of maximum rating. In addition, significant differences were found between the time to first response in each video ($p < 0.001$) and the time of maximum rating (p = 0.016). *Post hoc* tests showed that the AV and LS videos' times to first response are significantly lower than CM video time to first response ($p < 0.001$ and $p = 0.023$ respectively); and the time of maximum rating of the LS video is significantly higher than the AV video's time (p = 0.027). No significant differences were found between mean rating, time for minimum response, number of responses and the difference between the

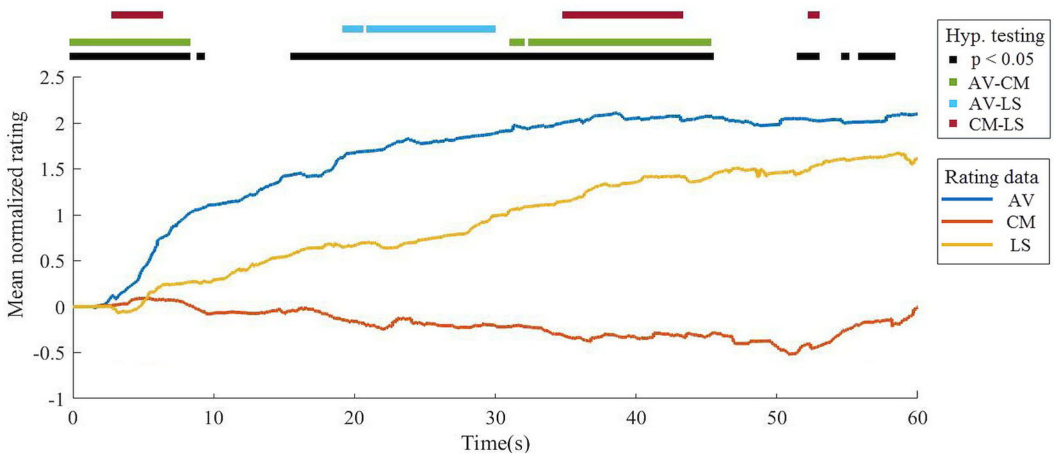

FIGURE 3 | Comparison of mean accumulated normalized ratings (ANRs) by video. AV, adventure video; CM, comedy video; LS, landscape video.

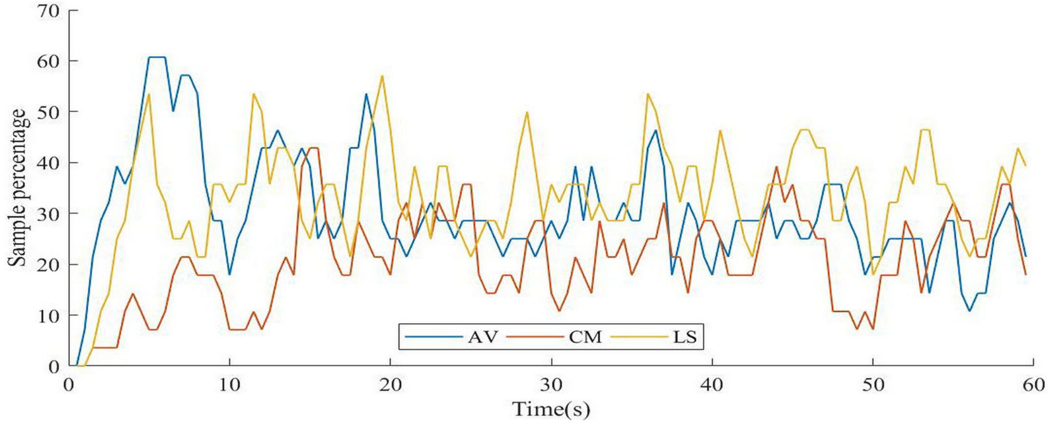

FIGURE 4 | Sample percentage of response on each second. AV, adventure video; CM, comedy video; LS, landscape video.

minimum and maximum ratings. Results are presented in further detail in **Table 1**.

Significant differences in liking were found among each video for nearly 65% of the video's total duration, more specifically at the following intervals: 0–8.129 s; 9.023 s to 9.172 s; 51.66 s to 52.77 s; 54.85 s to 54.91 s and 56.04 s to 58.17 s, as presented in **Figure 3**. *Post hoc* tests have shown significant differences between all pairs in at least some moment in time. More specifically, AV-CM videos: at 0–8.129 s, 31.27 s to 31.87 s, 32.61 s to 43.91 s and 44.3 s to 45.13 s, approximately 34.62% of the stimuli duration, with a mean difference of 1.45 ± 0.889 points; AV-LS videos: at 19.4 s to 20.4 s and 21.2 s to 29.74 s, approximately 15.96% of the stimuli duration, with a mean difference of 0.702 ± 0.371 points; and CM-LS videos: at 3.008 s to 6.121 s; 35.01 s to 43.11 s and 52.47 s to 52.77 s, approximately 18.91% of the stimuli duration, with a mean difference of −0.680 ± 0.571 points. No significant differences were found between the global median of each video ($\chi^2_{(2)} = 4.357, p = 0.113$).

Sample Percentage of Response

AV video presented a mean sample percentage of the response of 30% ± 11% on each second, with a maximum of 61% between 5.5 s and 6.5 s, which is the moment just after the scene in which a rollercoaster goes downhill for the first time. The CM video presented a mean sample percentage of the response of 20% ± 9% in each second, with a maximum of 43% between 15.5 s and 16.5 s, which occurs during a scene in which acupuncture needles are being placed on the character. Regarding the LS video, the mean sample percentage was 34% ± 10% in each second, with a maximum of 57% between 19.5 s and 20.5 s, when a scene appears that features a beautiful landscape of tundra, river, and mountains on the horizon. The results for each video are presented in **Figure 4**.

Moving Rating Sum

The maximum mean rating for the AV video was 1.36 ± 2.5 points at 5.75 s, corresponding to the same scene with the highest sample percentage of response; in

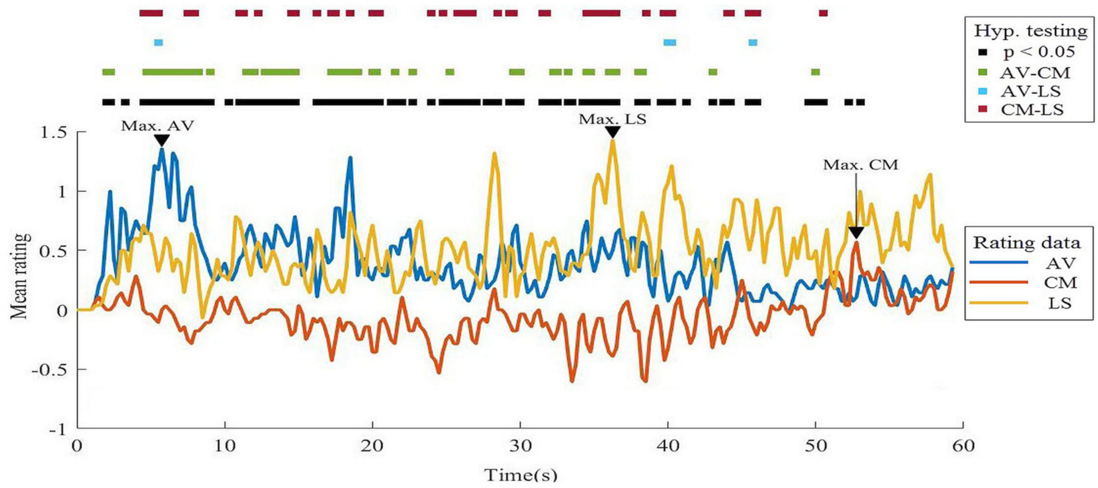

FIGURE 5 | Comparison of mean likeability ratings on overlapped 500 ms epochs. AV, adventure video; CM, comedy video; LS, landscape video.

TABLE 1 | Results of Friedman test with *post hoc* comparing subjective liking measurements.

	Mean AV	Mean CM	Mean LS	$\chi^2_{(2)}$	Sig.	AV-CM Sig.	AV-LS Sig.	CM-LS Sig.
Mean rating	0.38 ± 0.27	-0.06 ± 0.18	0.51 ± 0.27	0.271	0.873	–	–	–
Min. rating	-1.46 ± 1.71	-2.75 ± 3.2	-1.36 ± 1.61	8.614	0.013	0.04	1	0.158
Max. rating	3.71 ± 3.6	2 ± 1.96	4.43 ± 4.98	6.506	0.039	0.285	0.098	1
Min. time (s)	21.09 ± 18.5	21.57 ± 17	21.63 ± 18.7	0.13	0.937	–	–	–
Max. time (s)	13.27 ± 10.2	26.05 ± 19	22.82 ± 14.5	8.243	0.016	0.082	0.027	1
Time to first response	4.178 s	13.646 s	5.078 s	20.857	<0.001	<0.001	0.164	0.023
Number of responses	19.5	18.5	22	4.321	0.115	–	–	–
Max–min rating difference	5.18 ± 3.98	4.75 ± 3.98	5.79 ± 4.6	0.271	0.873	–	–	–

the case of the CM video, the maximum mean rating was 0.57 ± 1.77 points at 52.75 s, which corresponds to the moment when the character has to decide whether to jump onto a safety net while his body is covered with needles or stay in a building on fire. Finally, in the LS video, the maximum mean rating was 1.43 ± 2.31 points at 36.25 s, which corresponds to a scene showing a stunning landscape with colorful flowers, mountains, and a lake. Significant differences were found in 47% of the duration of the stimulus. *Post hoc* tests showed differences between AV-CM, in 23%, AV-LS in 2% and CM-LS in 21% of the stimuli duration. The mean pair difference was 0.591 ± 0.339 points in AV-CM, 0.587 ± 0.354 points in AV-LS and -0.331 ± 0.390 points in CM-LS. The results for each video are presented in **Figure 5**.

Regression Models

Adventure

A multiple linear regression was run to predict the likeability of the AV video based on EEG and ECG data. The multiple regression model significantly predicted the likeability rating for adventure, $F_{(2,25)} = 6.822$, $p = 0.004$, adj. $R^2 = 0.301$, RMSE = 1.95. Two variables added statistically significant results to the prediction $p < 0.05$: beta power in C4 and P4. Regression coefficients and standard errors can be found in **Table 2**.

Comedy

A multiple regression was run to predict the likeability of the CM video from EEG, ECG and ET data. The multiple regression model statistically significantly predicted the likeability rating on comedy, $F_{(1,26)} = 14{,}079$, $p = 0.001$, adj. $R^2 = 0.326$, RMSE = 1.91. Only one variable added significant results to the prediction $p < 0.05$: alpha power in Fp2. Regression coefficients and standard errors can be found in **Table 3**.

Landscape

A multiple regression was run to predict the likeability of the landscape video from EEG, ECG, and ET data. The multiple regression model significantly predicted the likeability rating for the LS video, $F_{(6.21)} = 5.304$, $p = 0.002$, adj. $R^2 = 0.489$, RMSE = 1.91. Six variables added significant results to the prediction $p < 0.05$: alpha power in P4, F8, and Fp2; beta power in C4 and P4 and pupil size. Regression coefficients and standard errors can be found in **Table 4**.

DISCUSSION

The study of the affective reactions induced by complex stimuli such as videos and the dynamics of its psychophysiological correlates over time can be a challenging, yet important, task. Videos are among the most engaging and expensive media products and the use of time-dependent methods to assess

TABLE 2 | Summary of multiple regression analysis of the likeability induced by the adventure video.

	Coef.		Std Coef.			Beta C.I. (95%)	
	Beta	**Standard error**	**Beta**	***t***	***p*-value**	**Lower threshold**	**Upper threshold**
Intercept	3.917	0.716		5.471	<0.001	2.443	5.392
C4 beta	2×10^{-4}	69×10^{-6}	0.468	2.903	0.008	58×10^{-6}	34×10^{-5}
P4 beta	19×10^{-5}	8×10^{-5}	0.392	2.431	0.023	3×10^{-5}	36×10^{-5}

Coef: coefficients. Std: standardized.

TABLE 3 | Summary of multiple regression analysis of the likeability induced by the comedy video.

	Coef.		Std Coef.			Beta C.I. (95%)	
	Beta	**Standard error**	**Beta**	***t***	***p*-value**	**Lower threshold**	**Upper threshold**
Intercept	3.794	0.668		5.685	<0.001	6×10^{-6}	2.422
Fp2 alpha	-9×10^{-5}	25×10^{-6}	−0.593	−3.752	0.001	-14×10^{-5}	-4×10^{-5}

Coef: coefficients. Std: standardized.

TABLE 4 | Summary of multiple regression analysis of the likeability induced by the landscape video.

	Coef.		Std Coef.			Beta C.I. (95%)	
	Beta	**Standard error**	**Beta**	***t***	***p*-value**	**Lower threshold**	**Upper threshold**
Intercept	4.209	0.875		4.808	< 0.001	2.388	6.029
P4 alpha	5×10^{-5}	69×10^{-6}	0.502	3.216	0.004	2×10^{-5}	9×10^{-5}
F8 alpha	-2×10^{-5}	8×10^{-5}	−1.287	−4.373	< 0.001	-4×10^{-5}	-13×10^{-6}
Fp2 alpha	-8×10^{-5}	69×10^{-6}	−0.448	−2.632	0.016	-15×10^{-5}	-2×10^{-5}
C4 beta	3×10^{-4}	8×10^{-5}	0.569	2.53	0.019	5×10^{-5}	10×10^{-5}
P4 beta	-25×10^{-5}	69×10^{-6}	−0.442	−3.004	0.007	-4×10^{-4}	-34×10^{-5}
Pupil size	−4.022	1.803	−0.541	−2.23	0.037	−7.773	−0.272

Coef: coefficients. Std: standardized.

affective reaction fluctuation scans provide valuable information which is not observable through conventional methods. This study is among the first to employ this kind of technique, providing a proof-of-concept on how to assess likeability and its psychophysiological correlates in three stimuli with marked contextual differences.

Subjective Liking Assessment

The results of the first phase have shown that there are distinct patterns among each video, which reflect the videos' narrative and semantic natures. The AV video presents results that could be described as following a rational curve trend, with a fast rating increase in the beginning of the presentation followed by a progressive deceleration towards the end of the video. This pattern suggests that the video produces an increase in arousal in the beginning, which is accompanied by a higher frequency of responses compared to the other video modalities, followed by a habituation phase, in which we observe a decrease in the responses. The rating curve of the LS video resembles a line with a constant increase rate; this pattern suggests that it is positive-valenced stimuli, presenting lower arousal than the AV video.

The physiological pattern underlying the duration of the CM video resembles a polynomial curve, beginning with few responses until 15 s, then establishing a descending pattern until nearly 50 s, when inversion occurs, presenting a fast rating increase. This three-phase pattern is common in comedy narratives: the presentation of the characters and the context happens in the beginning and then consecutive events create a minor tension, which is liberated by the comedic "gag" itself (Neale and Krutnik, 1990).

According to the incongruity-resolution theory, humor is based on a two-stage process: incongruity detection, which involves the detection of an incongruous element among two or more compatible events (e.g., a character who is in building on fire, has his body covered with needles and has to jump onto a safety net to save himself); and resolution, in which the incongruent element is linked in a meaningful way to rest of narrative, resolving the incongruity, e.g., the character has to choose between dying or facing a great deal of pain, (Uekermann et al., 2007). In this sense, humor processing involved in comedy videos is highly dependent on the informational aspects of the narrative, which encompasses several elements of social cognition, such as role comprehension, Theory of Mind, understanding of context, understanding of sociocultural norms (Uekermann et al., 2007; Vrticka et al., 2013; Chan et al., 2016) along with affective reactions and executive functions. These points taken together would explain why the time for the first response was up to three times longer than the other two videos, in which affective reactions related to excitement (in the case of the AV video) and aesthetic appreciation (in the case of the LS video) were involved.

Over 50% of the sample for the AV video presentation responded between 5.5 and 6.5 s. This pattern is explained by the high increase in the mean accumulated rating at the beginning of the video, followed by its decrease at the end. The LS video presented the highest mean rating response, with four peaks in the transition between scenes, in which nearly 50% of the sample responded, resembling a sawtooth pattern. Taking this into account, perhaps if the video was comprised of a single scene, this pattern would have been different. Interestingly, for the AV video, the participants tended to make the greatest number of evaluations at the beginning of the video. The CM video presented a percentage of overall response of about 10% less than the other videos, suggesting that comedy involves cognitive and social elements that might be more influenced by individual variability, resulting in less response concomitance, a pattern aligned with the literature (Vrticka et al., 2013; Chan et al., 2016). The results showed that for all videos, there is at least one moment in which more than 40% of the sample responded at the same second, indicating that the time-dependent approach is sensitive and valid to assess group trends over time.

The third and final phase allowed for a detailed investigation of liking at each instant of the video, particularly at moments of maximum and minimum ratings. In keeping with the previous results, the adventure video presented two peaks at the beginning of the video, indicating that these moments were marked with a higher frequency of responses.

The landscape video presented the highest maximum rating. This indicates that a peak of phenomenological well-being derives from calmer and less demanding stimulus, which may be determined by semantic qualities or by the context, as one may argue that in an experimental setting, a relaxing stimulus becomes particularly rewarding. Regarding the comedy video, there were three moments in the middle of the narrative with a greater frequency of responses of negative valence. On the other hand, a higher density of positive responses was observed at the end of the narrative, during the comedic "gag," corroborating the results found in the other analyses.

Physiological Measures

Electroencephalography

The variable selection for EEG data analysis was made using variables which had some representation in the field, according to our systematic review (submitted). We opted for this approach to deal with overfitting issues and allow direct comparisons with the literature, which was particularly important, given that application of this method to evaluate the psychophysiological correlates of liking videos is innovative.

Univariate analyses presented significant differences in most of the selected variables. The ones with the greatest difference between the EEG power in maximum and minimum ratings were theta in F1 for the adventure, alpha in P4 for the comedy and theta in P4 for the landscape video. These results are aligned with previous findings relating frontal asymmetry and parietal asymmetry, which are consistent with emotional regulation involved in approach-withdraw processing and valence coding (Davidson and Tomarken, 1989; Schellberg et al., 1990; Vecchiato et al., 2010, 2011; Koelstra et al., 2012).

The results for the adventure video are coherent with the literature on affective reactions induced by videos (Schellberg et al., 1990; Vecchiato et al., 2010, 2014; Koelstra et al., 2012; Kortelainen et al., 2015; Güzel Aydin et al., 2016), especially in terms of variables that represent valence and arousal, except for beta in Fp2 (Koelstra et al., 2012), indicating that these variables are associated with liking encoding in this thematic category, at least from the indicators that have already been mapped. In contrast, only six of 17 EEG variables in the comedy video presented significant results that were consistent with the literature in affective reactions induced by videos, more specifically: theta in F1, alpha in P4, alpha and gamma in F2, beta in F2 and P3, being the first four variables mainly involved in valence processing (Schellberg et al., 1990; Vecchiato et al., 2010; Silberstein and Nield, 2008; Vecchiato et al., 2014; Koelstra et al., 2012; Kortelainen et al., 2015) and the final two involved in the processing of both valence and arousal dimensions (Koelstra et al., 2012; Kortelainen et al., 2015). As applied to the AV video, the landscape video presented only three variables that were not aligned with the literature, more specifically: theta in F7, alpha in F8 and beta in C4, with the first variables related to valence (Schellberg et al., 1990; Vecchiato et al., 2010, 2011, 2014) and the last one to arousal processing (Koelstra et al., 2012).

Discrepancies in the literature are expected, given both the wide range of factors that were analyzed and the time-dependent method employed for subjective liking assessment. The ability to collect evaluative responses over time avoids methodological limitations of processes resulting from overall rating at the end of the video, since this tends to dismiss the impact of the intermediary events and give disproportional importance to the beginning and end of the video (Vallar and Papagno, 1986; Baddeley, 2010).

In that vein, the comedy video presented more discrepant results, which, at least to a certain point, may be a consequence of the traditional methodologies that access likeability at the end of the video (Fernández et al., 2012). The adventure and landscape videos presented results that agreed with the literature for approximately 80% of the evaluated variables. This is likely the case because the results did not measure the participant's interest at a very specific moment (e.g., the gag, as found in the comedy video).

Electrocardiography

Univariate analyses showed significant differences in PCR for adventure and comedy, with inverted results for each video; a higher cardiac frequency preceding the maximum rating and lower frequency preceding the minimum rating for the adventure video and the opposite for the comedy video. The increase in cardiac frequency is usually associated with an increase in levels of arousal in response to an stimulus (Fernández et al., 2012), and its association to valence is still controversial; some authors found positive correlations (Gomez et al., 2005; Codispoti et al., 2008; Kortelainen et al., 2015) while others found negative correlations (Vecchiato et al., 2010, 2014; Golland et al., 2014). In this article, the higher likeability scores in adventure was associated with an increase in arousal before the response, which is compatible with the perspective that the more exciting an adventure video, the better it is.

On the other hand, it is possible that in the CM video, the increase in arousal preceding the lower ratings was associated with negative valence feelings, such as anger, tension, and distress. Considering the content of the CM video, it is plausible to argue that such feelings were experienced at different levels by the participants due to their own subjectivities in terms of the context. The video selected for this experiment presented scenes in which one of the characters was receiving acupuncture treatment, with half of his body covered by needles. The story climax occurs when a fire starts breaks out in the building and he must decide whether he will jump through a window onto a safety net held by firefighters, piercing his whole body, or stay in the building. Thus, the increase in arousal could be a response to the increase in expectation and distress evoked by the scene. In this sense, the deceleration of the cardiac frequency might be associated with the relaxation after the climax, elicited by the gag, or even comparison to a more neutral state.

Eye Tracking

Univariate analyses showed significant differences in pupil diameter for landscape and comedy. In both cases, this suggests smaller diameters were associated with higher ratings. This finding was also verified by Bradley et al. (2008) in a seminal study of affective reactions to images. Also, it is worth noting that the latency in the CM video is approximately 400 ms lower than in the LS video. Pupil size is also related to cognitive workload (Just et al., 2003), since the cognitive demand of resources involved in judging a comedy must be higher due to the aforementioned aspects, it is reasonable that the latency and pupil diameter to be larger in this video.

Predicting Time-Dependent Subjective Likeability

The adoption of a multiple regression linear model, a classical technique, relied on its clear interpretability of the weights of each predictor over the dependent variable, directly answering the questions of "what is the best combination" and "what is the corresponding importance of each physiological measure to predict liking for stimuli with distinct semantic categories while using a time-dependent technique." All models presented significant results and were able to explain the difference between the maximum and minimum rating with 30% more accuracy than by chance (adj. $R^2 > 0.3$).

In the final adventure model, two variables presented higher importance: beta in C4 and beta in P4, respectively with a time delay of 1367 ms and 1055 ms. The relative weight of beta in C4 was slightly higher than in P4. According to the literature, the increase of beta in the right central and parietal region is related to both arousal processing and valence encoding (Schellberg et al., 1990; Koelstra et al., 2012; Kortelainen et al., 2015). In this sense, according to the correlates obtained using non-time-dependent measures, both variables are representative of valence and arousal, indicating a strong association of these dimensions with the AV video, suggesting that beta in the right centro-parietal area can be a relevant indicator for investigating liking in videos where high arousal and valence are positively correlated.

ECG was excluded from the final model for its redundancy with other variables. Couto et al. (2015) investigated changes in evoked cardiac responses related to affective stimuli and found significant results on the right parietal region. In this sense, it is possible that the electrical activity in this region could be redundant to the ECG activity, which corroborated the "V" shape relationship when considered alone.

Despite the initial comedy model being the only one to include all physiological measures (EEG, ECG, and ET), it was the one that presented a final model which needed the fewest variables to explain the differences in minimum and maximum liking. Indeed, with only the information on the spectral power in alpha in Fp2 at 688 ms before the rating response, it is possible to predict the likeability score with more than 30% accuracy beyond chance. Interestingly, our results are contrary to the literature (Schellberg et al., 1990; Vecchiato et al., 2010, 2011, 2014), indicating that for this type of video, the increase of alpha in the right frontal region is actually inversely correlated to the valence score.

In contrast to the comedy video, the landscape final model was the one with more variables. The relative importance of each variable in ascending order was: beta in P4, alpha in Fp2, alpha in P4, pupil size, beta in C4 and alpha in F8. Beta in C4 and alpha in P4 presented positive coefficients, whereas the other variables presented negative coefficients. Individually, beta in C4 and P4 are associated with valence and arousal processing (Koelstra et al., 2012), a negative correlation between the rating and beta in P4 can represent lower arousal, following the inverse logic of the adventure video. Alpha in P4 was also associated with valence processing (Schellberg et al., 1990; Koelstra et al., 2012; Kortelainen et al., 2015). In contrast to the literature, our findings show an inverse relationship between alpha power increase in the right frontal region and likeability ratings (Schellberg et al., 1990; Vecchiato et al., 2010, 2011, 2014). The landscape final model was the only one to employ measures other than those derived from the EEG, and as on the univariate analysis, the pupil size has shown an inverse relation to the likeability rating.

A Time-Dependent Method for Assessing the Physiological Correlates of Liking

To our knowledge, only one study evaluating the physiological correlates of affective reactions induced by videos made concomitant subjective evaluations along with the presentation of the stimuli (Golland et al., 2014). However, the method employed by Golland et al. (2014) have two main differences from the one presented in this study: (1) the assessed variable in our study was likeability, whereas their study evaluated emotional arousal; and (2) their equipment registered ratings ranging from 0 and 270°, with lower and upper thresholds, whereas our equipment allowed the participants to give ratings without any predefined limit, allowing analysis using individual evaluative intervals.

The search for objective measures of liking is still not possible without the employment of declarative measures, at least for experimental control. In this sense, the use of evaluation techniques which allow the assessment of variability along time can provide a new ground for affect detection. Our results indicate that the employment of time-dependent measures can provide more information regarding semantic and other time-dependent features of the stimulus, such as its narrative aspects, which cannot be assessed by the overall evaluation approach mainly used in the field. Notwithstanding, the time-dependent approach is much more complex and time-consuming, needing different processing steps to be conducted. However, it may provide insightful information from the dynamic changes of liking along the stimulus presentation. In this sense, researchers should consider whether to use this approach, based on their objectives.

The chosen categories were an adventure, a nature landscape, and comedy, as they present a clear narrative and structure, however, the methodological approach presented in this study could be extended to any video. We believe that this approach can be applied to the evaluation of the physiological correlates of other psychological phenomena, such as discourse reliability, sensorial perception, etc., as long as it can be understood by the subject as one single dimension. Additionally, as the methodology is based on internal differences for the same stimuli, it can be better suited for videos which are not so discrepant in terms of their valence and arousal.

Study Limitations

Regarding the study design and sample, there are common limitations related to correlation and exploratory studies. The first aspect is the sample size and its uniform nature, which makes generalization of the results difficult. Another limiting aspect regarding the sample is that the analyses did not consider gender differences, due to the sample size and imbalance of groups.

Regarding the stimuli selection, a potential limitation of this study is that only one 1-min video was selected for each category, without referring to a normative database, such as the Emotional Movie Data Base (EMDB; Carvalho et al., 2012) or Database for Emotional Analysis using Physiological Signals (DEAP; Koelstra et al., 2012), since the videos in these databases were collected from music video clips or Hollywood movies, there would be a high probability that the participants had already seen it and therefore biasing their evaluation.

Regarding the physiological measures, each modality has its own strengths and weaknesses. Therefore, by employing them together, both advantages and disadvantages were added together (that is, the limited spatial resolution of the EEG, loss of ET acquisition and muscle artifacts in ECG, just to name a few), which resulted in loss of information, given that only acceptable data was used in the study. Despite using the same monitor settings throughout the entire experiment, it was not possible to correct the brightness in all scenes across stimuli, which may have influenced the pupillometry.

In regard to the likeability assessment, as with any self-reported measure, the results are widely influenced by individual variability and this study was not an exception (in fact, applying time-dependent measurements makes individual variability stack over time). In addition, there was no comparison with any standard evaluation methods for likeability assessment, such as SAM, or even a global scaling technique.

In terms of the predictive model, it is important to note that not all existent indicators found in the literature were investigated [such as skin conductance level (Vecchiato et al., 2010) or body posture (Ramsøy et al., 2017)] but just a few indicators derived from EEG, ECG and ET which had a clear correspondence in the literature. Nevertheless, it was a necessary measure to employ the linear regression. Finally, we employed multiple regression linear models, which assume that there is no measurement error, and therefore its results should be taken with a certain caution.

Final Comments and Future Directions

With this study, our team attempted to advance one of the most traditional questions of psychology, which is liking, from an updated perspective, in which data is highlighted and the phenomenon is approached in a more careful and methodologically-sound fashion. We proposed the use of a time-dependent approach for mapping the psychophysiological correlation of subjective liking, induced by stimuli with marked semantic differences. This allowed the investigation of narrative nuances for each stimulus, along with many other time-related aspects, providing a noteworthy alternative to the traditional approach used in most studies in the field of affective psychophysiology and affective computing.

Some observations can be determined based on the findings:

1. First, is the need for a methodological refinement phase, enlarging the sample and allowing other groups to collaborate and work on this data, following the steps of DEAP (Koelstra et al., 2012) and EMDB, applying this method on other constructs and stimuli.
2. After the consolidation of the method for the healthy adult population, it is possible to make comparisons with individuals of other cultures, ages, and clinical populations.
3. Another branch would be applying these methods for audiovisual and marketing research, given the potential of this technique to improve advertising and non-advertising videos.
4. Finally, a generalist approach should not be used when assessing audiovisual narrative appreciation from a scientific perspective, given that different thematic categories may demand diverse affective parameters of evaluation. The case of horror movies may be especially interesting, as reactions traditionally associated with displeasure can be argued to be, at least in principle, drivers of positive appreciation for such a category.

CONCLUSION

This is the first study to employ time-dependent methods to assess likeability of videos and its psychophysiological correlation in a multimodal (i.e., EEG, ECG and ET) and context- sensitive setup. The use of a time-dependent measure can provide valuable information, such as narrative nuances, sample response over time and scene relevance, which cannot be assessed through traditional methods. Conversely, it is possible to establish the physiological correlates of likeability in a much more precise manner, by pinpointing the most relevant moments of the video and using their corresponding physiological patterns in order to evaluate not only which combination of indicators has the best predictive power, but also the optimal time interval. Despite the methodological limitations of the current study, these findings have important implications for the field of consumer and affective neuroscience, suggesting that there is a considerable difference in the psychophysiological correlates of stimuli with different contextual properties and that the use of time-dependent methods to assess videos should be considered as best practices.

ETHICS STATEMENT

This study was carried out in accordance with the recommendations of the National Health Council of Brazil (CNS 510, from April 07 of 2016), ethics committee for research involving human beings from the Institute of Psychology of the University of Sao Paulo. The protocol was approved by the ethics committee for research involving human beings from the Institute of Psychology of the University of Sao Paulo. All subjects gave written informed consent in accordance with the Declaration of Helsinki.

AUTHOR CONTRIBUTIONS

HA: study design, data processing and analysis, manuscript writing. MC: study design, manuscript review. JG and PS: manuscript review. EO: data processing and analysis, manuscript review. AD: study design, manuscript writing, manuscript review.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fnhum.2019.00073/full#supplementary-material

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Group-Level Neural Responses to Service-to-Service Brand Extension

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Brand extension is a marketing strategy leveraging well-established brand to promote new offerings provided as goods or service. The previous neurophysiological studies on goods-to-goods brand extension have proposed that categorization and semantic memory processes are involved in brand extension evaluation. However, it is unknown whether these same processes also underlie service-to-service brand extension. The present study, therefore, aims to investigate neural processes in consumers underlying their judgment of service-to-service brand extension. Specifically, we investigated human electroencephalographic responses to extended services that were commonly considered to fit well or badly with parent brand among consumers. For this purpose, we proposed a new stimulus grouping method to find commonly acceptable or unacceptable service extensions. In the experiment, participants reported the acceptability of 56 brand extension pairs, consisting of parent brand name (S1) and extended service name (S2). From individual acceptability responses, we assigned each pair to one of the three fit levels: high- (i.e., highly acceptable), low-, and mid-fit. Next, we selected stimuli that received high/low-fit evaluations from a majority of participants (i.e., >85%) and assigned them to a high/low *population-fit* group. A comparison of event-related potentials (ERPs) between population-fit groups through a paired *t*-test showed significant differences in the fronto-central N2 and fronto-parietal P300 amplitudes. We further evaluated inter-subject variability of these ERP components by a decoding analysis that classified N2 and/or P300 amplitudes into a high, or low population-fit class using a support vector machine. Leave-one-subject-out validation revealed classification accuracy of 60.35% with N2 amplitudes, 78.95% with P300, and 73.68% with both, indicating a relatively high inter-subject variability of N2 but low for P300. This validation showed that fronto-parietal P300 reflected neural processes more consistent across subjects in service-to-service brand extension. We further observed that the left frontal P300 amplitude was increased as fit-level increased across stimuli, indicating a semantic retrieval process to evaluate a semantic link between S1 and S2. Parietal P300 showed a higher amplitude in the high population-fit group, reflecting a similarity-based categorization process. In sum, our results suggest that service-to-service brand extension evaluation may share similar neural processes with goods-to-goods brand extension.

Keywords: brand extension, event-related potential, P300, neuromarketing, EEG decoding

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INTRODUCTION

Brand rises as one of the key concepts in the contemporary marketing as consumers become increasingly exposed to a variety of brands, which affect their current and future purchase behavior. Brand extension is a marketing strategy that utilizes well-established brand names for new offerings (Loken and John, 1993). The offering is generally provided in a form of goods or services, which possess clearly distinct characteristics. Compared to goods offering, service offering portrays characteristics of inseparability of production and consumption, heterogeneity (i.e., difficulty to support consistent quality for individual consumers), intangibility, perishability, and a lack of ownership (Zeithaml et al., 1985; Iacobucci, 1998; Lovelock and Gummesson, 2004). Often, these characteristics make it more difficult for consumers to categorize service offerings rather than goods offerings.

To understand how consumers recognize, categorize, and evaluate brand extension, a number of cognitive neuroscience studies have investigated behavioral and neural responses to brand extension (Ma et al., 2007, 2008, 2010, 2014; Wang et al., 2012; Jin et al., 2015; Fudali-Czyż et al., 2016; Shang et al., 2017; Yang et al., 2018). In particular, a series of event-related potential (ERP) studies have suggested that a predominant cognitive process during brand extension evaluation is to compare a given product's attributes to the corresponding attributes in brand memory. This process seemingly elicited ERP waveforms such as N270 (Ma et al., 2007) or P300 (Ma et al., 2008). Other investigations demonstrated the effect of emotions (Ma et al., 2010), unconscious categorization processing (Wang et al., 2012), and a stimuli presentation scheme (Ma et al., 2014) on neural responses to brand extension. Recent research has targeted broader aspects of brand extension by looking into brand extension strategies for launching a new brand (Jin et al., 2015), cultural differences (Fudali-Czyż et al., 2016) and the effect of logos (Shang et al., 2017). However, all of these studies have focused only on goods-to-goods brand extension. Because of the distinction in characteristics of service offerings (e.g., heterogeneity and intangibility), it is likely that a different cognitive processing would be involved in the evaluation of service-to-service brand extension.

Accordingly, Yang et al. (2018) recently investigated neural correlates of service-to-service brand extension evaluation. To study neural responses to brand extension, it is often necessary to provide brand extension stimuli with varying levels of fit between parent brand and extended offering. While fit levels between brand and goods offering can be objectively determined by the choice of the category of goods, it is more challenging to determine fit levels for service extension due to a difficulty in categorizing service offering. To address this issue, the investigators proposed a data-driven individual stimuli grouping method in which stimuli were grouped based on participant's own behavioral response. As a result, high-fit and low-fit groups of stimuli varied across individual subjects. The ERP results showed that the frontal P300 (Novelty P3a) amplitude was higher for the low-fit than high-fit groups, suggesting that consumers recognized a low-fit service extension as a target stimulus in the evaluation task and evaluated service-to-service brand extension based on improbability, not approvability. That is, the subjects evaluated a given brand extension stimulus based on its level of improbability. However, the individual stimuli grouping method proposed in this previous study could not show participants' neural response to common brand extension stimuli (for example, see **Figure 2**). Nonetheless, brand marketers may pursue to understand common response in a population of consumers when they evaluate a specific service-to-service brand extension.

Therefore, in the present study, we aim to find neural responses on stimuli commonly considered as high/low-fit to the population. For this purpose, we suggest a new stimuli grouping method. This method categorizes a stimulus as a high population-fit group if the acceptability across participants are universally high, a low population-fit group if those are universally low, or undetermined if mixed. In doing so, we can find neural responses of all participants to the same stimuli. In addition, we conduct a decoding analysis by estimating a population-fit level from the ERP amplitudes in order to demonstrate that which ERPs components indeed represent common neural responses across subjects. For this purpose, we build and train a classifier by using the data of subjects and then apply the trained classifier to the data of a novel subject to examine whether the classifier could accurately classify ERPs of the novel subject – labeled as the leave-one-subject-out cross validation. If the classifier could successfully estimate the population-fit level for a novel subject, it would mean that feature set of the classifier represent common neural responses across subjects.

MATERIALS AND METHODS

Participants and Materials

In the experiment, 37 university students without any neurological disorders have participated, and they were prohibited to smoke or drink for a day before the experiment (18 Female, mean age 22.1 $\pm$ 0.33 years) (Yang et al., 2018). This study was carried out in accordance with the recommendations of Institutional Review Board of the Ulsan National Institute of Science and Technology (UNISTIRB-16-29-G) with written informed consent from all subjects. All subjects gave written informed consent in accordance with the Declaration of Helsinki. The protocol was approved by the Institutional Review Board of the Ulsan National Institute of Science and Technology. Among 37 participants, the data of one participant whose experiment was interrupted and four participants who did not answer the survey questions correctly were excluded from the analysis. In addition, the data of 13 participants were additionally excluded during the EEG analysis due to following issues: (1) the EEG data of four participants contained too much noise despite artifact reduction using the independent component analysis (ICA) method; and (2) the AR data of nine participants failed to give the minimum number of trials for each fit group (the minimum of 12 trials). Consequently, the EEG and behavioral data of a total of 19 participants were analyzed (nine males, mean age of 20.6 $\pm$ 0.48 years old).

A

Parent brand type	Parent brand (S1)	Extended service (S2)
E-commerce	11st G-market	TV home shopping channel, Fashion magazine, Travel agency, Insurance service, Marketing consulting, Newspaper, Food delivery
Finance	Kookmin bank Shinhan bank	TV economy channel, Economy magazine, Education, Legal counseling, Hospital, Simultaneous interpretation, Airline
Airline	Korean air Asiana airline	Travel agency, Travel information magazine, Simultaneous interpretation, Accommodation reservation, TV documentary channel, Rent-a-car, Education
Accommodation	Lotte hotel Walkerhill hotel	Club, Catering, Travel information magazine, Travel agency, Legal counseling, Hospital, Finance

B

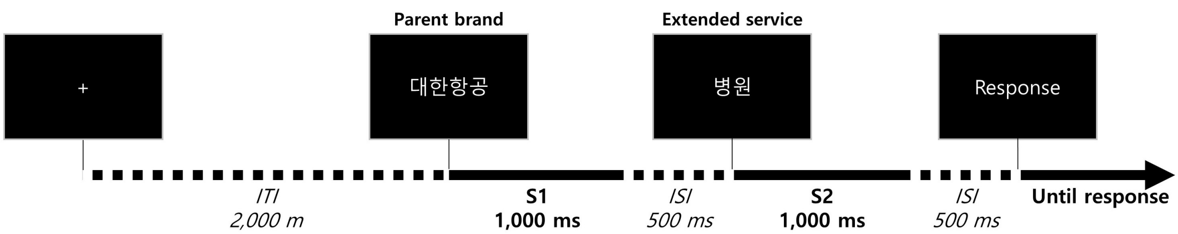

FIGURE 1 | Experimental stimuli and task. **(A)** Experimental stimuli. A total of 56 stimuli pairs were pre-determined. **(B)** Experimental task. Participants were given successive brand extension stimuli including a parent brand name and extended service name, then asked to respond whether that brand extension is acceptable or not.

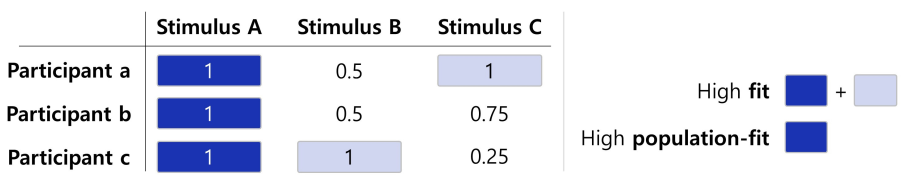

FIGURE 2 | An illustration of a difference between the stimuli grouping methods for fit level and population-fit level. Fit level derives from an acceptance rate of one participant, while population-fit level is a result of acceptance rates (AR) of participants. In the figure, for example, the numerical value indicates an acceptance rate of stimulus from each participant. Each stimulus is labeled as high (AR = 1) or low (AR = 0), and mid (the other) fit level. Stimulus C is considered as high-fit level only for participant a. On the contrary, stimulus A is considered as high-fit for most of participants. Therefore, stimulus A is also considered as high population-fit level.

Fifty-six experimental stimuli consisting of eight parent brand names (S1) and seven extended service names per brand (S2) were collected in previous service brand extension studies (Lei et al., 2004; Brown et al., 2011; Arslan and Altuna, 2012). Specifically, we first determined four service categories (E-commerce, finance, airline, and accommodation) and then selected two popular brands from each of four categories. From *post hoc* interviews, we confirmed that participants were familiar to all of the selected brands and services. Extended services varied according to service category (see **Figure 1A**).

Experimental Task

The S1–S2 paradigm with an explicit task, which has been used for previous brand extension studies (Ma et al., 2007, 2008), was adopted in our experiment (**Figure 1B**). In a single trial of the task, one of the eight parent brand names (S1) was presented, followed by one of the seven corresponding extended service names (S2). After the presentation of S2, participants were asked to respond using a keyboard (with their right hand) whether the provided extension was acceptable or not with a binary response (i.e., yes or no). Stimulus presentation time, inter-stimulus-interval (ISI) between S1 and S2, and inter-trial-interval (ITI) were set to 1,000, 500, and 2,000 ms, respectively. All the combinations of S1–S2 were randomly provided in a block of trials so that there were 56 trials performed per block. The experiment included one training block followed by four test blocks with break times (∼30 s on average) between blocks. As a result, each S1–S2 combination was repeatedly presented four times. At the end of the experiment, participants were asked to answer seven questions for each of the following brand extensions: acceptance for brand extension, expected quality to the extended service, preference to the extended service, similarity between service of parent brand and extended service, attitude toward brand extension, attitude toward parent brand, and involvement toward extended service.

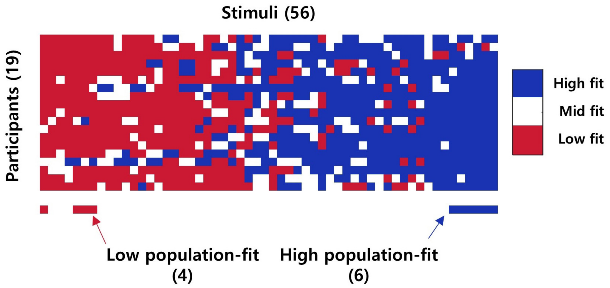

FIGURE 3 | Stimuli grouping result. The image above indicates the fit level of each stimulus for each participant. The red bar below indicates low population-fit stimuli, while the blue bar indicates high population-fit stimuli. Only stimuli which was considered as high/low fit level for more than 85% of participants were selected as high/low population-fit stimuli.

EEG Recordings

The experiment was conducted in a dim and electrically shielded room. The visual stimuli showing brand names or extended services were displayed on a 27-inch monitor (QH2700-IPSMS, Achieva Korea, Incheon, Korea) positioned at an approximately 60-cm distance from participants' eyes. While participants performed the task, their scalp electroencephalography (EEG) signals were measured (band-pass filtering: 0.05–100 Hz, sampling rate: 500 Hz) using a 31-channel wet-electrode EEG recording system (actiCHamp, Brain products GmbH, Gliching, Germany) at the following electrode locations: FP1, FPz, FP2, F7, F3, Fz, F4, F8, FC9, FC5, FC1, FC2, FC6, FC10, T7, C3, Cz, C4, T8, CP5, CP1, CP2, CP6, P7, P3, Pz, P4, P8, O1, Oz, and O2 (in accordance with the International 10/20 system). An additional electrode was applied to the left mastoid (TP9) as a ground. The EEG signals were on-line referenced to the right mastoid (TP10). Impedance of every electrode was maintained below 10 kΩ during the recordings.

Stimuli Grouping Method

In the previous study (Yang et al., 2018), authors compared ERPs between high and low-fit stimuli. However, this analysis has limitations in that the result is response to different stimulus among participants. Therefore, we wanted to show neural response to common stimuli among participants. As a result, we developed the term "*population-fit level*" from "fit level." First, we calculated an acceptance rate (AR) by averaging four behavioral response (1 or 0). In next, we grouped stimuli in low (AR = 0), high (AR = 1), and mid (the others) according to AR score by participant. Finally, we collected only stimuli which was assigned to high/low fit for most of participants (>85% of participants in our case) and named them as high/low population-fit groups (see **Figure 2**). This stimuli grouping method yielded a low population-fit set with four stimuli (i.e., Kookmin Bank – hospital, Shinhan Bank – hospital, Shinhan Bank – airline, and Lotte Hotel – legal counseling) and a high population-fit set with six stimuli (i.e., Shinhan Bank – economy magazine, Korean Air – travel information magazine, Korean Air – simultaneous interpretation, Korean Air – TV documentary channel, Asiana Airline – simultaneous interpretation, and Asiana Airline – TV documentary channel; **Figure 3**).

Data Analysis

The behavioral data acquired in the experiment besides acceptance of brand extension included reaction time (RT) and responses to seven questions after the experiment. We compared RT and survey responses between two sets of population-fit stimuli using a paired t-test ($N = 19$).

The recorded EEG signals were first filtered with 0.5 and 50-Hz cutoff frequencies using a FIR filter. Next, eye blinks and muscle artifacts were removed using the ICA method with visual inspection. Then, EEG epochs were extracted from a 1,250 ms data segment (−250 ∼ 1,000 ms) time-locked to the onset of the second stimulus (S2) and corrected to each baseline (i.e., −250 ∼ 0 ms time-locked to the onset of S2). ERP waveforms of high or low population-fit groups were obtained by averaging EEG data over the epochs of all the six stimuli (high population-fit) or four stimuli (low population-fit), for each channel and each participant. To evaluate statistical differences in ERPs between the population-fit groups, mean amplitudes of N2 (170 ∼ 230 ms time-locked to the onset of S2) and P300 ERP components

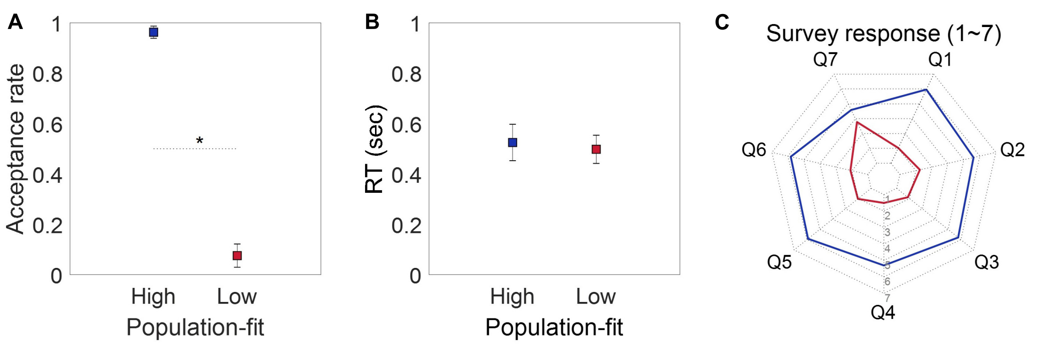

FIGURE 4 | Behavioral results. **(A)** Population-wise acceptance rate of participants. **(B)** Population-wise reaction time of participants when evaluating whether a given brand extension was acceptable or not by pressing a keyboard. **(C)** Population-wise survey responses for seven questions. Paired t-test showed significant difference between two groups for every survey category.

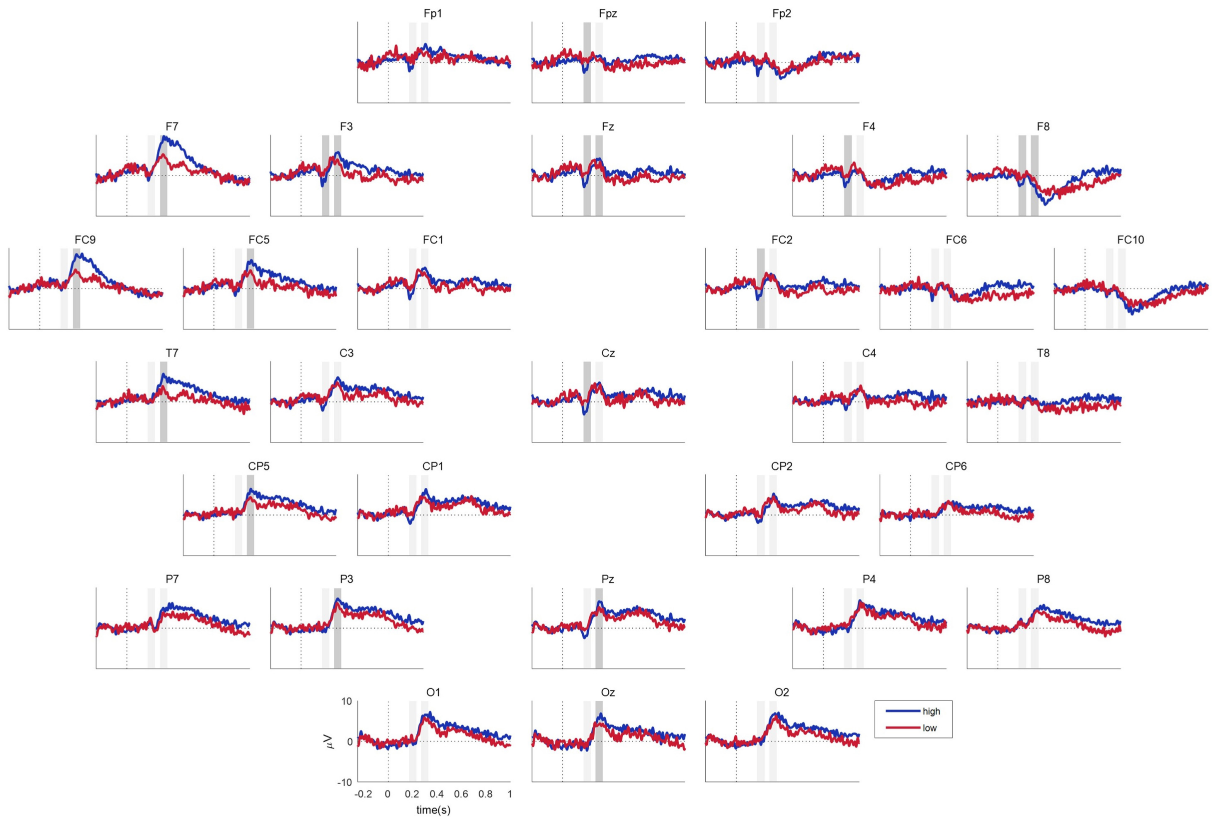

FIGURE 5 | Event-related potential results. Blue and red lines indicate responses to the high and low population-fit stimulus sets, respectively. Gray boxes indicate time segments for N2 and P300 (from left to right), among which darker gray boxes denote a significant difference in the mean amplitudes between the high and low population-fit sets.

(270 ∼ 330 ms time-locked to the onset of S2) were compared between the high- and low population-fit groups using a paired *t*-test ($N = 19$), at each EEG channel.

Decoding Analysis

To find key component to describe neural responses to service-to-service brand extension, we conducted a decoding analysis with ERP waveforms. There have been many studies that conducted decoding analyses with a single-trial ERP waveform (e.g., Simanova et al., 2010; Li et al., 2012). However, our decoding analysis was different from these previous studies as it was designed to predict the population-fit level (i.e., either high- or low-fit) by building a classifier using selected EEG features from grand average ERP waveforms. We first extracted the feature of the mean amplitudes of N2 and P300, respectively, at every channel. Then, we selected channels which showed a significant difference in these amplitudes between the high and low population-fit groups (paired *t*-test, $p < 0.05$). This yielded seven channels for N2 and 10 for P300, respectively (see section "Decoding Results"). Next, we created a feature set of N2 (i.e., 7-dimensional feature vector) and that of P300 (i.e., 10-dimensional feature vector) individually, and fed each set to a decoding algorithm in order to examine which component provided better features for decoding. To verify the effect of dimensionality of a feature space, we also created a higher dimensional feature vector by combining both N2 and P300 features into a new feature set, resulting in an additional 17-dimensional feature vector. To evaluate decoding accuracy, a leave-one-subject-out cross validation scheme was used: among data from nineteen participants, we trained the classifier using those of eighteen participants and predicted the population-fit with those of the remaining participant, which was repeated nineteen times. The linear kernel support vector machine (SVM) was used as a classifier model.

RESULTS

Behavioral Results

A paired *t*-test showed a significant difference in the fit evaluation responses to the high [mean (M) = 0.963, SE = 0.0242] and low (M = 0.0757, SE = 0.0462) population-fit stimulus sets ($t_{(18)}$ = 18.062, $p < 0.001$; **Figure 4A**). A paired *t*-test for the RT showed no difference between the high (M = 0.525 s, SE = 0.0722) and low (M = 0.498 s, SE = 0.0561) population-fit sets ($t_{(18)}$ = 0.547, p = 0.591; **Figure 4B**). On the contrary, paired *t*-tests for each of the seven survey responses showed significant

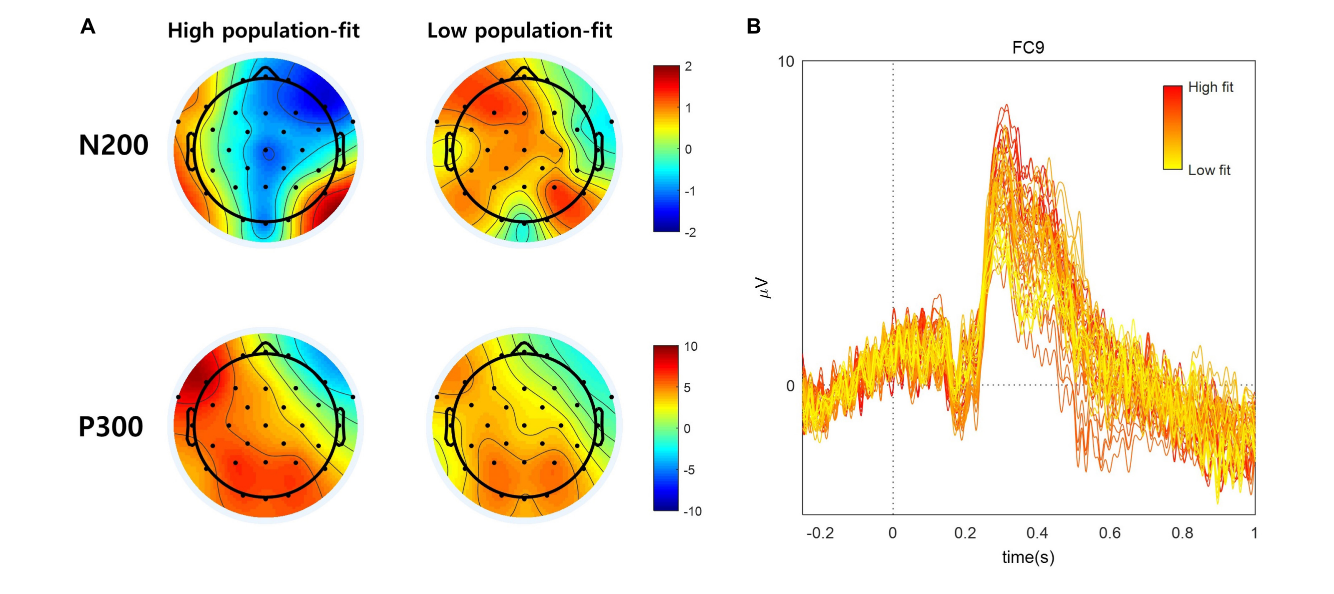

FIGURE 6 | (A) EEG topographic map of high and low population-fit stimuli during N200 (170–230 ms) and P300 (270–330 ms). **(B)** Fifty ERP subsets according to the ratio of high-fit response at the left frontal area (i.e., FC9).

differences between the high and low population-fit sets for all questions (*ps* < 0.05; **Figure 4C**).

ERP Results

The ERPs obtained from the present study showed the prominent waveform of the N2 (170 $\sim$ 230 ms) ERP component over the fronto-central area and the P300 (270 $\sim$ 330 ms) ERP component over all scalp locations except for the right fronto-central area (**Figure 5**). We further compared a spatial pattern of the mean N2 and P300 amplitudes between the high and low population-fit sets using topographic maps (**Figure 6A**). It was shown that the mean N2 amplitudes at fronto-central channels were more negative in response to high population-fit stimuli than low population-fit stimuli. The mean P300 amplitudes were higher over left fronto-parietal channels in response to high population-fit stimuli than low population-fit stimuli. Additionally, we sorted stimuli according to the ratio of high-fit response and grouped each six stimuli by shifting the window, resulting in 50 stimulus subsets and corresponding ERPs (**Figure 6B**). These ERPs showed that the left frontal P300 amplitudes tended to gradually increase from low population-fit to high population-fit stimulus subsets.

To quantify the observations, a paired t-test was conducted for each EEG channel data. It revealed significant differences in the mean N2 amplitude between the high and low population-fit sets at FPz, F3, Fz, F4, F8, FC2, and Cz (**Supplementary Table 1**). In addition, the test showed significant differences in the mean P300 amplitude between the two population-fit sets at F7, F3, Fz, F8, FC9, FC5, T7, Cp5, P3, Pz, and Oz (**Supplementary Table 2**).

Decoding Results

Features of the mean N2 amplitude were extracted from ERP waveforms at seven electrodes (i.e., FPz, F3, Fz, F4, F8, FC2, and Cz). Features of the mean P300 amplitude were extracted from ERP waveforms at ten electrodes (i.e., F7, F3, Fz, FC9, FC5, T7, CP5, P3, Pz, and Oz). The decoding analysis resulted in the classification accuracy of 78.95% when using the mean P300 amplitude feature set, 60.53% when using the mean N2 amplitude feature set, and 73.68% when using the combined feature set (**Figure 7**). Note that the chance level was 50% as we extracted features from a single ERP waveform for each class (i.e., high and low population-fit classes) in each participant.

DISCUSSION

A previous study investigated service-to-service brand extension and its neural substrates (Yang et al., 2018). However, this previous study grouped stimuli based on the subjective evaluation of a fit level, leading that the analyzed neural activities of individual participants were responses to different stimuli. In contrast, the present study suggested a new stimuli grouping method to create the same set of stimuli based on the ratio of participants' common evaluation (i.e., population-fit level). As such, we could analyze the neural responses to identical stimuli across all participants.

The newly suggested grouping method did not have an effect on the behavioral result (**Figure 4**), whereas the EEG result was substantially affected by it. The remarkable difference in the ERP waveform was the spatial pattern of P300 and the absence of N400. In Yang et al. (2018), right frontal P300 and N400 amplitudes were prominent in response to high individual-fit brand extension stimuli. However, in the present study, fronto-central N2 and left frontal-parietal P300 amplitudes were prominent and significantly distinguished between high and low population-fits (**Figure 5**). Although there was also a significant difference of P300 amplitudes at the right frontal EEG channel

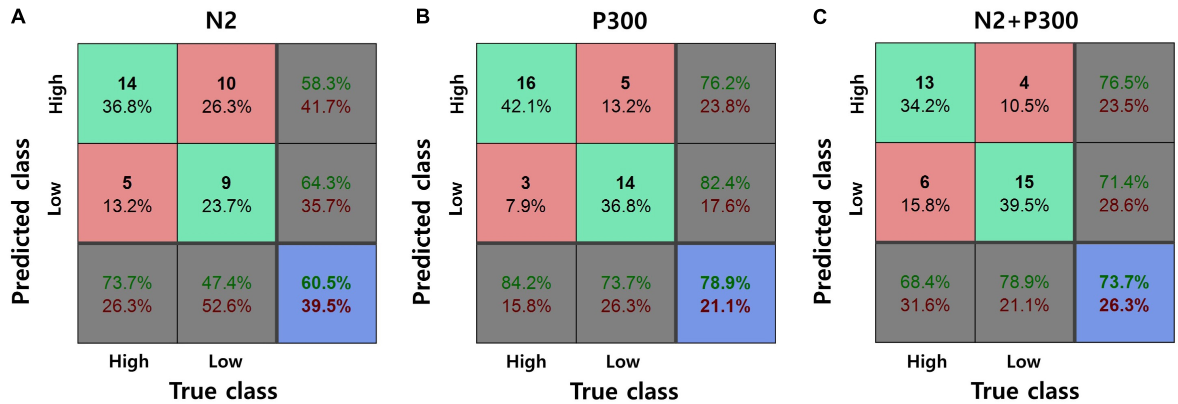

FIGURE 7 | Classification result with the selected ERP features at channels of interests. **(A)** Mean N2 amplitude. **(B)** Mean P300 amplitude. **(C)** Both mean N2 and P300 amplitudes.

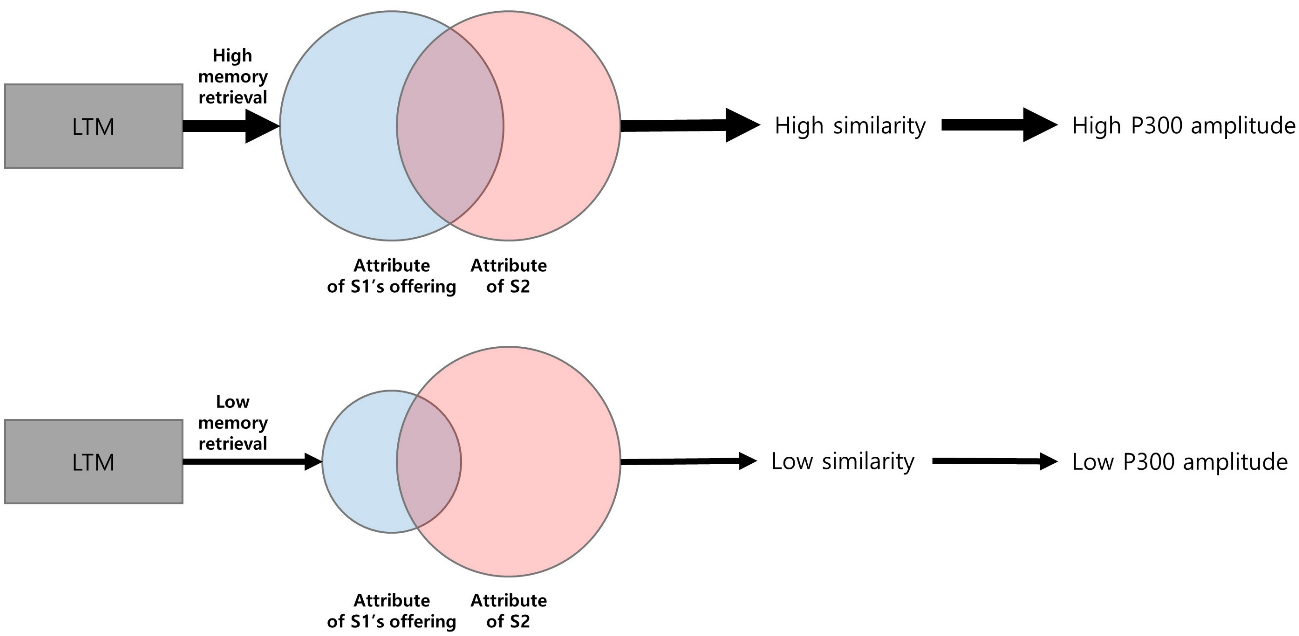

FIGURE 8 | Conceptual diagram of memory-categorizing processing.

(i.e., F8), right frontal P300 was not considered in further analysis because its amplitude level and waveform did not fit well to the standard definition of P300.

Our ERP result revealed that the mean N2 amplitudes at fronto-central channels (e.g., FPz, Fz, and Cz) were significantly different between population-fits, showing larger negative amplitudes for high population-fit stimuli. In the decoding analysis (**Figure 7**), the classification accuracy with the mean N2 amplitude was only 60.53%, whereas that with the mean P300 amplitude was 78.95%. This result indicates that N2 response was not consistent enough across subjects and not appropriate, whereas P300 is an appropriate ERP component to be a key component investigate the common response in consumers when evaluating service-to-service brand extension.

Ma et al. (2008) reported that parietal P300 was elicited in both high- and low-fit conditions but with a larger amplitude for the high-fit condition, indicating that categorizing processing could induce P300. They suggested that larger parietal P300 amplitudes might be associated with a larger degree of perceived similarity of attributes between parent brand's goods and extended goods. Our study showed the same result at the parietal area, which depicts that there is also the similarity-based categorizing processing in service-to-service brand extension evaluation. In our result, the parietal P300 showed dominance in the left hemisphere. This pattern might be related to the activity of the left anterior temporal pole (Brodmann area 38), which is shown to be more active with complete sentences than scrambled ones, playing a potential role in the composition of sentence meaning (Vandenberghe et al., 2002). Therefore participants might understand a relationship between S1 and S2 more naturally for high population-fit stimuli, akin to the composition of a sentence.

Our results also revealed the left dominance of P300 amplitudes at the frontal area. This spatial pattern was more remarkable for the high population-fit condition (**Figure 6A**). In addition, the P300 amplitude at the left frontal area (i.e., FC9) showed a trend that gradually increases along the ratio of high-fit response (**Figure 6B**). According to previous research, Brodmann area 47, which is close to the left frontal area, is related to language-related semantic retrieval processing (Zhang et al., 2004; Lehtonen et al., 2005) Therefore, left frontal dominance of P300 amplitudes might be related to semantic retrieval processing during the evaluation of brand extension. Overall, we conceptualize a two-stage brand extension evaluation model as follows: in the first stage, memory retrieval of parent brand elicits attributes of parent brand's offering; and in the second stage, similarity of attributes between brand's offering and S2 is perceived (**Figure 8**). If brand extension successfully retrieves abundant attributes of parent brand's offering, it would be more likely that those attributes and the attributes of S2 will become more similar, which is reflected by larger P300 amplitudes. Although Ma et al. (2008) suggested a similar categorization model, our study could extend the scope of models from only goods-to-goods brand extension to including service-to-service brand extension.

Our result that high population-fit stimuli revealed higher frontal P300 amplitude provides us background knowledge to extract significant features to predict brand extension fit levels using EEG. The prediction is meaningful in that it helps marketers know consumers' attitude toward the brand extension before launching. However, in most real situations, marketers would want to know the fit level of a specific brand. Despite diverse analyses, this study yet conducted a group-wise fit-level analysis, rather than the individual stimulus-level. Therefore, in extended research in the future, the experiment should be designed to consider the stimulus-level analysis. In addition, to overcome the limitation that the connection between our results and some references are not strong due to a difference in apparatus, functional magnetic resonance imaging (fMRI) should be used to investigate the evaluating process of brand extension.

CONCLUSION

The present study investigated common neural processes in a group of people when they evaluated service-to-service brand extension. To find common neural responses, we applied a new stimuli grouping method in which the high-, or low-fit brand extension stimuli were selected based on population-fit, not individual evaluations of fit levels. The analysis of ERPs in response to the high- and low-population fit stimuli showed a significant difference in left fronto-parietal P300 amplitudes between population-fit stimulus groups where the P300 amplitude was higher for the high population-fit group. In addition, the P300 amplitude tended to increase as a fit level increased. A decoding analysis showed the low inter-subject variability of the P300 amplitude, demonstrating that we could decode the fit level from the P300 amplitude of one subject using a classifier trained using the data of all other subjects. Our results suggest that left fronto-parietal P300 may provide neural evidence for the acceptability of a new service-to-service brand extension to a population of consumers, which may involve semantic memory retrieval and similarity-based categorization.

DATA AVAILABILITY

The datasets generated for this study are available on request to the corresponding author.

ETHICS STATEMENT

This study was carried out in accordance with the recommendations of Institutional Review Board of the Ulsan National Institute of Science and Technology (UNISTIRB-16-29-G) with written informed consent from all subjects. All subjects gave written informed consent in accordance with the Declaration of Helsinki. The protocol was approved by the Institutional Review Board of the Ulsan National Institute of Science and Technology.

AUTHOR CONTRIBUTIONS

TY participated in all aspects of the work, designed and conducted the experiment, analyzed the data, and wrote the manuscript. S-PK oversaw the study and managed every part of the research. Both authors read and approved the final manuscript.

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SUPPLEMENTARY MATERIAL

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The Influence of the Consumer Ethnocentrism and Cultural Familiarity on Brand Preference: Evidence of Event-Related Potential (ERP)

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The tendency of customers' preference to their local brands over the foreign ones is known as consumer ethnocentrism, and it is an important issue in international marketing. This study aims at identifying the behavioral and neural correlates of Consumer Ethnocentrism in the field of brand preference, using event-related potential (ERP). We sampled subjects from two ethnic groups, a Chinese ethnic group and a sub-Saharan Black African group from Zhejiang University. The subjects faced two sequential stimuli, S1 followed by S2. S1 consisted of 40 pictures of 20 Chinese and 20 Black Africans people wearing traditional clothes, and S2 consisted of 40 fake brand-logos which were divided randomly into two groups of 20 each. The subjects were informed that the people in S1 purchased and recommended the products with the brand-logos presented in S2, and the subjects were asked to rate their preference degree toward these logos. The brand-logos were called the "in-group recommended logos" if the recommenders in S1 were the same race as the subjects, otherwise, the "out-group recommended logos." The results revealed that the race of the brand-logo recommender highly impacted the Chinese subjects' preference for the brand-logos. The N200 component elicited by the in-group recommended logos were significantly lower than those elicited by the out-group recommended logos. Additionally, there was evidence that being familiar with foreign cultures reduced consumer ethnocentrism. The African subjects were familiar with Chinese people and adopted a Chinese culture, as a result, they did not differ in showing preferences between the in-group and out-group recommended logos.

Keywords: event-related potential, N200, consumer ethnocentrism, preference, neuromarketing, neuromanagement, branding, purchase intention

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INTRODUCTION

Consumer's tendency to buy a locally made good over a foreign product is known as consumer ethnocentrism (de Ruyter et al., 1998; Moon and Jain, 2002; Rand et al., 2009; Jiménez and San Martín, 2010). This conceptual phenomenon leads to making purchasing decisions that do not only depend on price-quality but also depend on the criterion of where the product comes from (Garmatjuk and Parts, 2015). Ethnocentrism is originally a sociological concept, and it shows the relationship between a group to which an individual belongs (in-group) and the group that the individual does not belong to (out-group; de Ruyter et al., 1998). A group is not limited to a social or racial segregation but could also be any other organization that an individual feels apart of, such as gender, ethnicity, religion, musical preferences, dressing styles (Hornstein, 1972; Fershtman and Gneezy, 2001; Platow and van Knippenberg, 2001; Levine et al., 2005; Stürmer et al., 2006; He et al., 2009; Rand et al., 2009), and it is a process which starts from childhood to adulthood (Ben-Ner et al., 2009). Individuals from a cultural collectivism like the Chinese and Africans often see their role as individuals in relation to the family or society that they identify themselves with and, therefore, support in-group members (Chen et al., 2002; Hustinx and Lammertyn, 2003; Kemmelmeier et al., 2006; Pierre and Matondo, 2012).

In the current study, the priming stimuli consisted of two ethnic group pictures, Black African and Asian Chinese people. Generally, during race facial differentiation the subjects have some difficulty in identifying the other races' face, which is known as other race effects (Sporer, 2001; Hugenberg et al., 2007). Some previous research that studied faces of an in-group and out-group race concluded that three event-related potential (ERP) components could be distinguished between in-group and out-group race faces, comprising the early negative component which reflects the face processing and peaking around 170 ms after the stimulus (N170), the negative wave recorded between 200 and 350 ms after the stimulus (N200), and the late positives potential appearing around 300 ms after the stimulus (P300; Dickter and Bartholow, 2007; Walker et al., 2008). Furthermore, the ERP components P200 and the N200 were linked with early attention processes while the P300 was associated with the evaluative categorization processes (Ito et al., 1998; Dickter and Bartholow, 2007; Walker et al., 2008). During the categorization of the in-group and out-group faces, the existing results showed that the own race faces elicited larger N200 at the frontal area while the other race faces elicited larger P200 and P300 at the parietal region (Dickter and Bartholow, 2007). Another experiment which used an in-group face, an out-group face and a non-face as stimuli found that N170 distinguished the face stimuli from the non-face stimuli, and the N250 elicited by the in-group faces was larger than that of the out-group faces (Ito et al., 2004). In addition, the same study revealed that only in the people with higher levels of prejudice the late-positive potential (LPP) peaking at partial electrode differentiated between the in-group and out-group faces (Ito et al., 2004). However, the familiarity and contact with the other culture-ethnic group could reduce all racial bias aspects (Malinowska, 2016). Previous researchers, for example, found that cultural familiarity and contact with other ethnicities reduced the racial bias in empathy (Xu et al., 2009; Zuo and Han, 2013). Moreover, after the training which aimed at increasing the level of familiarity with the other group race face, the amplitude of N250 for the other race group face was larger than before (Tanaka and Pierce, 2009). Meanwhile, the existing studies found that N170 could not differentiate between familiar and unfamiliar faces (Jemel et al., 2003; Tanaka et al., 2006). However, some previous studies suggested that the N250 elicited by familiar faces was connected solely to one semantic process which was related to familiar face identification (Bentin and Deouell, 2000), while during the interaction of familiarity and facial expression processing the familiar faces elicited a shorter P300 latency than the unfamiliar faces (Wild-Wall et al., 2008).

Related studies using neuroscience to investigate consumer ethnocentrism are scarce. Until now, most scholars have used a consumer ethnocentrism tendencies scale approach, which is composed of 17 items, to study consumer ethnocentrism (Shimp and Sharma, 1987). Although the concept of ethnocentrism refers to the preference of in-group over out-group products regardless of the group category (nation, ethnicity, etc.), in practice the majority of consumer ethnocentrism research focuses mainly on the nation-state group. For example, in different countries, consumers driven by patriotism tend to prefer local products over imported ones (Shimp and Sharma, 1987; Vida et al., 2008; Wise, 2017). Only a few studies used the category group, other than a nation-state, such as Vida et al. (2008) who distinguished between the in-group and out-group based on the culture-ethnic groupings. Moreover, consumer ethnocentrism could be driven by other factors than patriotism. These other factors could include perceived vulnerability to a threat (Wise, 2017), brand and product category (Balabanis and Siamagka, 2017) and cultural identity (He and Lu, 2015). The theory of planned behavior (TPB) is frequently used to predict the purchase intention and brand preference, which claims that attitude, subjective norms and the ability to do any specific behavior, determines the behavior intention (Ajzen, 1991). Typically, subjective norms are divided into two parts, the descriptive norm, and the conjunctive norm. Descriptive norm refers to an individual doing what the others do, i.e., the individual adopts the others' opinions and behaviors (Stok et al., 2014). Conjunctive norms are defined as what an individual should do, is determined by acceptable and unacceptable social group behavior (Stok et al., 2014). Although the original TPB did not distinguish between the two types of norms, the descriptive norm was nonetheless often used to predict the behavioral intentions (Borsari and Carey, 2003). The term social conformity was used widely by neuroscience scholars to describe the effect of the group opinion on individual behavior (Stallen and Sanfey, 2015). However, EEG studies found that the conformity related to the brain activities correlated to the two brain areas, the striatum and the ventromedial prefrontal cortex (Bartra et al., 2013; Stallen and Sanfey, 2015). On the other hand, several studies have linked EEG frontal asymmetries to consumer choice prediction and purchase intention (Ambler et al., 2004; Vecchiato et al., 2011). Besides, ERP components were associated with categorizing and evaluating stimuli, P300 (Polich, 2007) and N200 (Folstein and Van Petten, 2008) and most recently P200 and LPP (Ma et al., 2018). Furthermore, ERP component N200 and a weaker theta band was associated to purchase intention (Telpaz et al., 2015).

Cultural familiarity is a large topic which entails several dimensions (e.g., experience; Carneiro and Crompton, 2010).

Commonly, the number of previous visits to a destination was used as criteria to distinguish between the familiar and unfamiliar groups (Carneiro and Crompton, 2010; Prats et al., 2016). A tourist's previous visits and experiences influence the positivity of their satisfaction about the destination (Prats et al., 2016; Trianasari et al., 2018). Moreover, a tourist's familiarity has a positive impact on the image of the local products of the destination and induces a higher intention for consuming local products such as food (Seo et al., 2013). Furthermore, cultural sensitivity also positively and directly impacts the image of the destination and the visitors' satisfaction (Palacio and Martín-Santana, 2018). The cultural sensitivity measures the cultural openness, which refers to the willingness to communicate with people from different culture-ethnic groups and to experience their related objects (Sharma et al., 1995; Shankarmahesh, 2006; Mahon and Cushner, 2014). To the best of our knowledge, none of the consumer ethnocentrism scholars have explored the relationship between consumer ethnocentrism and cultural familiarity, while several studies have investigated the relationship between cultural sensitivity and consumer ethnocentrism (Sharma et al., 1995; Nguyen et al., 2008; Wang, 2018). Consumers with a high degree of cultural sensitivity are more positive and feel less threatened by the other culture-ethnic groups and consequently, such consumers prefer more of the imported products than the consumers with a lower degree of cultural sensitivity (Wang, 2018).

In this experiment, we sampled subjects from two groups consisting of Asian Chinese people who had never been outside of China and Black people of sub-Saharan African origin who have been international students in China for more than 1 year, respectively. In order to understand the effect of the cultural familiarity on consumer ethnocentrism based on ethnic-culture groupings and driven by descriptive norms, we applied an ERP experiment with the S1–S2 paradigm. S1 presented pictures of the two races with neutral facial expressions and wearing ethnically corresponding traditional clothes. The two race groups' pictures were then followed by S2, fake brand logos (S2) which were randomly divided into two groups, one corresponding to Chinese people's pictures (referred to as C-logo), and the others corresponded to the African people's pictures (A-logo). The subjects were informed that the people in S1 had bought the earphones and therefore recommended the brand-logo in S2 to them. The subjects were then asked to indicate their preferences for the logos. The logos were called the "in-group recommended logos" if the recommenders in S1 were the same race as the subjects, otherwise, the "out-group recommended logos."

Based on the above introduction, we hypothesized that cultural familiarity would modulate consumer ethnocentrism driven by descriptive norms, i.e., the impact of the recommendation of the race picture in S1 on the brand-logo in S2 was determined by the cultural familiarity of Chinese and African subjects. In Chinese subjects, the unfamiliarity to the African culture and people was expected to lead them to be more bias toward the Chinese than the African recommender in S1, which made the Chinese subjects prefer the C-logo more than the A-logo. In the African subjects, the familiarity with the Chinese culture and people reduced the racial bias in S1, thus no difference in preference was expected between the A-logo and C-logo.

MATERIALS AND METHODS

Participants

Twenty international male students who have lived in China for more than 1 year and identify themselves as being of Black ethnicity with sub-Saharan origin were engaged in the group of Black African subjects (age range = 19–37 years, M = 25.95, SD = 6.41), and 20 Asian Chinese males (age range = 20–32 years, M = 26.3, SD = 3.12) who identify themselves as being of Asian ethnicity and who have not traveled outside of China were enlisted to denote the Asian Chinese subjects in this study. The independent sample t-test revealed no significant difference of age between the two subject groups, $t_{(38)} = -0.157$; $p = 0.876$. Both Chinese and African subjects were students at Zhejiang University. The experiment was conducted at the Neuro-management lab, Zhejiang University. All subjects had normal or corrected to normal vision with no history of neurological or psychiatric abnormalities. This study was approved by the Neuromanagement Laboratory Ethics Committee at Zhejiang University. Written informed consent was obtained from all participants before the ERP experiment.

Stimuli

In the current study, the priming stimuli (S1) consisted of 40 pictures of 20 Asian Chinese and 20 Black Africans (equal number of males and females) with neutral facial expressions and wearing corresponding traditional clothes, which were chosen randomly from the Internet. All the people in the pictures stood up, simply extended their hands without a hand gesture, and had the same posture. The subjects were not familiar with race pictures and did not include celebrity pictures. These pictures were processed to have the same size and background using Adobe Photoshop 13.0.S2, consisted of 40 fake earphone logo pictures used in our previous study (Ma et al., 2017) and were divided randomly into two groups of 20 each, following Chinese pictures and African pictures, respectively, in the ERP experiment.

To test the stimuli, all subjects were asked to rate for the attractiveness of the race stimuli (S1) and preference of the logo stimuli (S2) on a 5-point scale (1 = very low to 5 = very high), after the ERP experiment section. The differences between the Chinese Race Picture and African Race Picture in attractiveness were rated by each subject group. And a significant difference was found in the Chinese subject group ($M_{Chinese-Picture} = 3.785$, $SD_{Chinese-Picture} = 0.446$; $M_{African-Picture} = 2.23$, $SD_{African-Picture} = 0.345$; $t_{(19)} = 17.162$, $p = 0.000$), while in African subject group there was no significant difference ($M_{Chinese-Picture} = 3.210$, $SD_{Chinese-Picture} = 0.65$; $M_{African-Picture} = 3.265$, $SD_{African-Picture} = 0.589$; $t_{(19)} = -0.704$, $P = 0.49$). In addition, The two groups of logos, i.e., C-logos and A-logos, were tested without priming stimuli in Chinese subjects in the previous ERP study, and no difference between the two logo groups was found (Ma et al., 2017). Thus we just asked the African subjects to rate the two groups of logos without priming stimuli, the paired sample t-test revealed that there was no difference in the preferences between the A-logos and C-logos (M = 2.798, SD = 0.33) and C-logos (M = 2.93, SD = 0.304), $t_{(19)} = -1.146$, $p = 0.266$.

The subjects' familiarity was measured by their previous visits to a destination according to previous studies (Carneiro and Crompton, 2010; Prats et al., 2016). Specifically, the Chinese subjects were asked; "Have you ever been to Africa?" The question required a binary response of Yes/No. If the answer was yes, then the follow-up question was "How long have you stayed in Africa?" The African subjects were asked the same questions about their visit to China. The result showed that all the Chinese subjects had never been to Africa, while all the African subjects were international students living in China for 16 months on average. The subjects were also given a cultural sensitivity scale (Loo and Shiomi, 1999; Nguyen et al., 2008) for supplementary analysis. The scale consists of five items Likert scaled (from 1 = strongly disagree to 5 = strongly agree). Cronbach's alpha of the five items was 0.74. The independent sample t-test of the culture sensitivity scale revealed that the African subjects had a higher mean score (3.8 $\pm$ 0.349) compared to the Chinese subjects (2.7 $\pm$ 0.358); $t_{(38)} = -9.828$, $p = 0.000$.

Experimental Procedures and EEG Recording

Figure 1 indicates a single trial in the ERP experiment. The stimuli were presented using the E-prime 2.0 software package (Psychology Software Tools, Pittsburgh, PA, USA). A fixation appeared at the beginning of each trial for 500 ms on a gray screen. Next, a picture of Chinese or African people (S1) was presented for 1,000 ms. Then a gray blank screen was presented randomly between 500 ms and 600 ms, and then, a picture of the logo (S2) was subsequently presented for 1,000 ms. The subjects were told that people appearing in the S1 pictures currently use and therefore recommend the earphones in S2 to them, and their task was to rank the logo in S2 from 1 (dislike a lot) to 5 (like a lot) using the mini keypad. After the rating, a 1,000 ms blank was presented at the end of each trial.

In total 80 trials were randomly presented to each subject in this experiment, i.e., 40 Race Pictures in S1 (20 Asian Chinese pictures, 20 Black African pictures) and then 40 logos in S2 (20 C-logos and 20 A-logos), presented to each subject twice.

EEGs were recorded (band-pass 0.05–70 Hz, sampling rate 500 Hz) with a NeuroScan SynAmps2 Amplifier (Scan 4.3.1, Neurosoft Labs, Inc., Sterling, VA, USA), using a 64-channel electro-cap with Ag/AgCl electrodes, in mounted according to the extended International 10-20 system and referenced to linked mastoids. Vertical and horizontal electrooculograms were recorded with two pairs of electrodes, one placed above and below the right eye, and another 10 mm from the lateral canthi. The electrode impedance was maintained below 5 kΩ during the experiment.

Data Analysis

EEG data were analyzed using the software NeuroScan version 4.3.1. The EOG artifacts were initially corrected, followed by digital filtering through a zero-phase shift (low pass at 30 Hz, 24 dB/octave). The EEGs were segmented for 1,000 ms in each epoch, 200 ms before the onset of S1 and S2 until 800 ms after the onset, respectively. The baseline corrected using the 200 ms before the stimulus onset. Trials that contained amplifier clippings, bursts of electromyography activity, or peak-to-peak deflection that exceeded $\pm$80 μV were excluded from the final average.

Based on visual inspection, the time window of P300 was chosen as 290–420 ms after the onset of the race picture (S1). Besides, P300 after the onset of S1 was observed over the parietal-occipital site that was similar to prior studies (Ito et al., 2004; Dickter and Bartholow, 2007). Thus, we selected the PO5, POZ, and PO6 for our analyses of P300. After the onset of the logo stimulus (S2), the time window of 200–350 ms was chosen for N2.

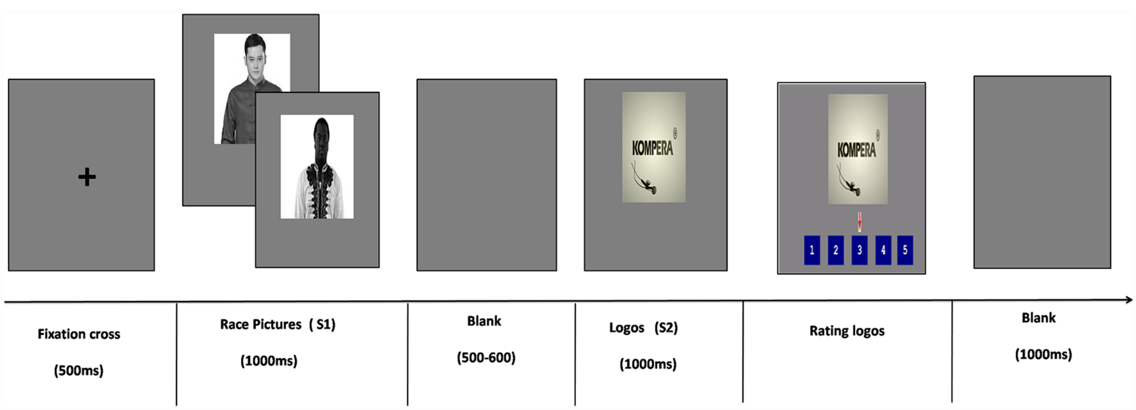

FIGURE 1 | The event-related potential (ERP) experiment procedure. Participants saw a Chinese Asian picture, or an African Black picture at first (S1), then a logo (S2). The subject is informed that the people in S1 purchased and positively recommended the logo in S2 to them. Their task was to rate logos using the mini keypad.

Considering that previous studies of product preference N2 components are generally distributed largely in the frontal and midfrontal regions (Telpaz et al., 2015), we therefore, chose the electrodes F3, FZ, F4, FC3, FCZ, and FC4 for the analyses of N2.

To analyze the neural response of stimuli in S1, we conducted a mixed-model ANOVA with Subject Groups (Chinese subjects vs. African subjects) as a between-subject factor and Race Picture groups (Asian Chinese people vs. Black African people) as a within-subject factor on P300. Whereas, to analyze the impact effect of S1 on brand-logos stimuli in S2, we performed a mixed ANOVA with the Subject Group as the between-subjects factor and Logo groups (C-logos vs. A-logos) as the within-subject factor on the N2 component. The brand-logos rating score was analyzed using a mixed-model ANOVA with the Subject Group (Chinese subjects vs. African subjects) as the between-subject factor and brand-logos Groups (C-logos vs. A-logos) as a within-subject factor. After the mixed ANOVA for both behavior and neural data, the paired sample *t*-tests were used to break down the interaction effects revealed in those ANOVA analyses (Raz et al., 2013). All the data related to this study are provided in **Supplementary Table S1**. The Greenhouse-Geisser and Bonferroni corrections were applied where appropriate.

RESULTS

For Race picture (S1) processing, the mixed-model ANOVA on the P300 component revealed that there were significant main effects for the Subject Groups ($F_{(1,38)}$ = 4.714, P = 0.036) and not for Race Pictures ($F_{(1,38)}$ = 2.911, P = 0.096). The interaction between the Race Picture and Subject Group was significant ($F_{(1,38)}$ = 10.076, P = 0.03). The paired sample analysis showed that the mean amplitude of P300 elicited by the Asian Chinese race pictures in the Chinese subject group (3.6142 μV $\pm$ 2.072) was significantly lower than that of the Black African race picture (5.19 μV $\pm$ 2.93) $t_{(19)}$ = −2.953, P = 0.008, whereas no significant difference in P300 elicited by the Asian Chinese race picture with that of the Black African race pictures was found in the African subject group $t_{(19)}$ = 1.303, P = 0.208, **Figure 2**.

According to the results of the mixed ANOVA on N2 for the logo stimuli (S2), as indicated by **Figure 3**, there was a significant main effect for the Subject Group ($F_{(1,38)}$ = 6.917, P = 0.012). While the main effect of the logo Picture was not significant ($F_{(1,38)}$ = 1.451, P = 0.236). In addition, the ANOVA showed a significant interaction effect between the Subject Group and the Logo Pictures ($F_{(1,38)}$ = 9.445, P = 0.004). The simple effect analysis revealed that in the Chinese subject group the N2 elicited by C-logos was significantly higher (−2.895 μV $\pm$ 3.504) than that by A-logos (−4.0928 μV $\pm$ 3.372), $t_{(19)}$ = 2.854, P = 0.01, whereas in the African subject group, no such significant difference was found ($t_{(19)}$ = −1.411, P = 0.174).

The Mixed-model ANOVA for logo rating (in the ERP experiment) revealed no significant main effects for Subject Groups ($F_{(1,38)}$ = 0.013, P = 0.909), moreover, there was no significant main effect for Logo Groups ($F_{(1,38)}$ = 2.041, P = 0.161). While there was a significant interaction effect of the Subject Group with Logo Groups ($F_{(1,38)}$ = 8.828, P = 0.005). To break down this interaction, a simple effect analysis showed that the C-logo rating scores in the Chinese subject group (3.016 $\pm$ 0.407) was significantly higher than the A-logo rating scores (2.798 $\pm$ 0.356), $t_{(19)}$ = 2.515, P = 0.021, whereas in the African subjects group no significant differences were found between A-logo and C-logo rating scores, $t_{(19)}$ = −1.592, P = 0.128. This result is presented graphically in **Figure 4**.

DISCUSSION

The present study sets out to investigate the influence of consumer ethnocentrism on brand-logo preference using the

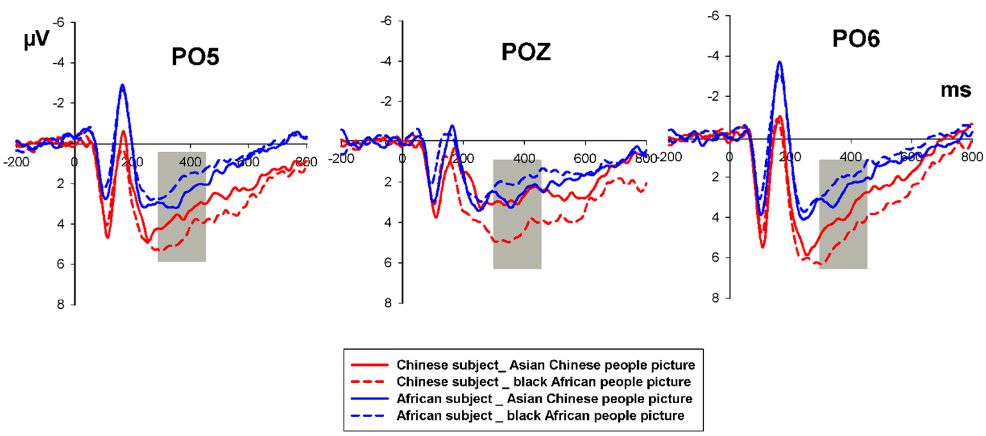

FIGURE 2 | Grand-averaged ERPs of P300 by Race Picture (S1) in the Chinese and African subject groups, respectively. The solid red line refers to Asian Chinese people pictured in S1 for the Chinese subject and the short-dash red line to Black African people pictured in S1 for Chinese subjects. The solid blue line refers to Asian Chinese people pictured in S1 for African subjects and the short-dash blue line to Black African people pictured in S1 for African subjects.

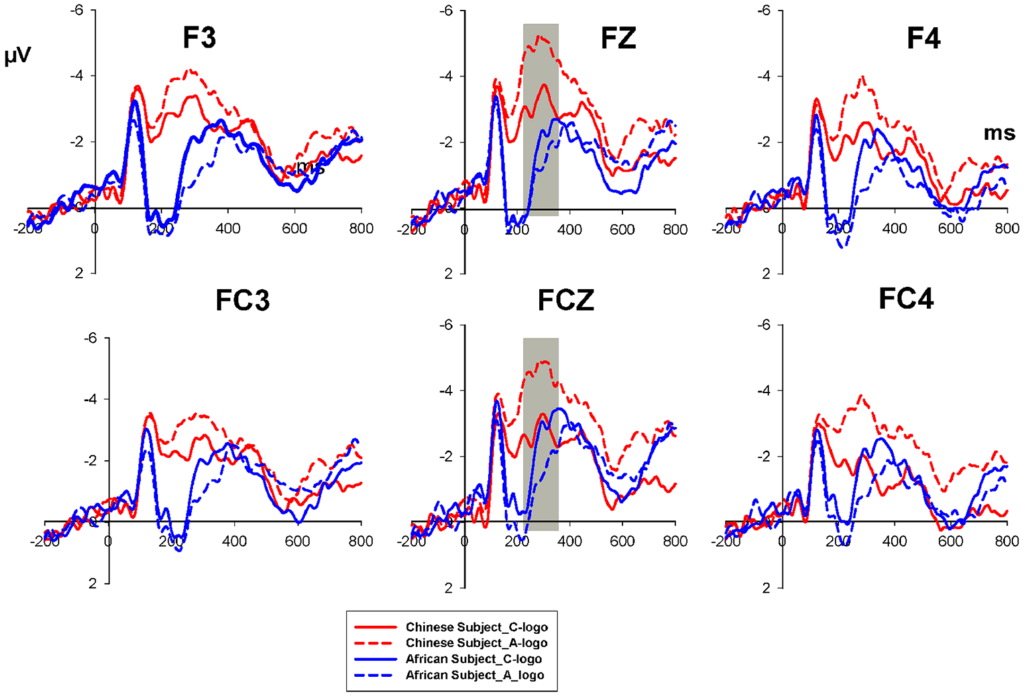

FIGURE 3 | Grand-averaged ERPs of N2 elicited by logo stimuli. The solid red line refers to C-logo for Chinese subjects and the short-dash red line to the A-logo for Chinese subjects. The solid blue line refers to C-logos for African subjects, and the short-dash blue line to the A-logo for African subjects.

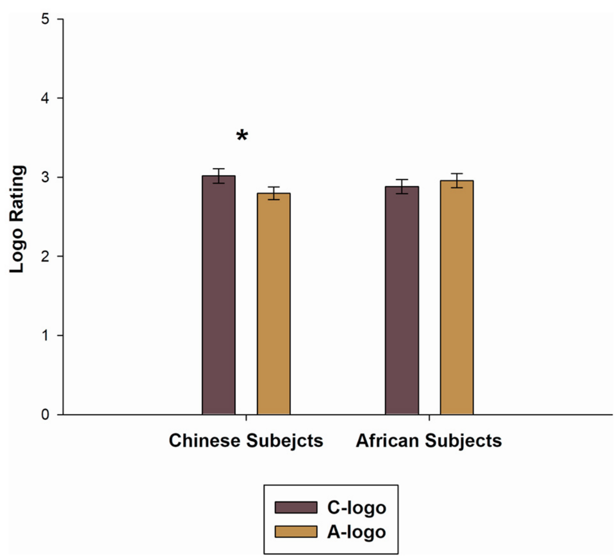

FIGURE 4 | The means of A-logo and C-logo rating scores for the Black African and Asian Chinese subjects. *Denotes a significant difference between the A-logo and C-logo rating for Chinese subjects.

ERP method. We recruited two subject groups, one consisting of Asian Chinese students and the other comprised of Black international students from sub-Saharan African countries living in China. The purchase behavior and the positive recommendation of the logos in S2 from Asian Chinese or Black African peoples in S1 were important determinants of their preferences but only in the Chinese subjects who had low familiarity with African culture, while the effect of the descriptive norm was not found in the African subjects who were familiar with Chinese culture because of their time spent living in China.

The neural response showed that the race picture (S1) evoked a neural bias against the other race group as indicated by P300. The mixed ANOVA on P300 showed the significant interaction between Subject Group and Race Picture (S1), and the simple analysis revealed that the out-group race picture (i.e., the people in S1 were not of the same race as the subjects) elicited a more positive P300 than the in-group race picture in the Chinese subject group, but no such effect was found in the African subject group. Some previous studies have indicated that the P300 was correlated with other race effects (Ito et al., 2004; Dickter and Bartholow, 2007; He et al., 2009; Tanaka and Pierce, 2009). The P300 was associated with the encoding of familiar and unfamiliar faces during the interaction of facial expression and familiarity processing (Wild-Wall et al., 2008). Therefore, the P300 in S1 could appear as a result of the encoding of the familiar and unfamiliar ethnic faces and clothes in the Race picture stimulus. Importantly, as previous literature revealed that only in the higher prejudice group the LPP could be differentiated between the in-group and out-group faces (Ito et al., 2004). Consistent with these findings, we found that the P300 at the similar brain region could be distinguished between the race pictures only in the Chinese subjects. Larger P300 elicited by out-group race pictures indicated that Chinese subjects are less familiar and have greater bias with African race than with their own race, which could also be supported by the self-reported cultural familiarity and sensitivity. However, the P300 results from African subjects did not provide evidence about the racial bias, which might be attributed to the long living time of African subjects in China.

The ERP component N2 elicited by C-logos was significantly smaller than that by A-logos among the Chinese subjects. A previous study found that N2 was associated with purchase intention, and the products with low or no preference elicited a more negative N2 amplitude than the high preferred product (Telpaz et al., 2015). Accordingly, the effect of descriptive norms on the brand preference was evident in Chinese subjects, i.e., the logos purchased and positively recommended by Asian Chinese people were perceived more favorable than the logos purchased and positively recommended by Black African people. However, in the Black African subjects, no significant difference in N2 was found between the A-logo and C-logo, indicating that the African subjects had a similar preference to logos purchased and recommended by Chinese people and African people. The rating scores for the A-logos and C-logos were in line with the N2 result. The influence of the Race Picture on the logo rating was obviously observed, especially for Chinese subjects. Chinese subjects gave a higher rating score for the in-group recommended brand-logo (C-logo) than the out-group recommended brand-logo (A-logo), while the African subjects showed no significant difference between the rating scores of the A-logo and C-logo. These results might be attributed to the African subjects' familiarity with both Chinese and African culture, which reduced the effect of descriptive norms on brand preference. A previous multicultural study which investigated the Chinese cultural adoption for international students in China concluded that international students adopted the Chinese culture over time (An and Chiang, 2015). According to the cultural familiarity and sensitivity measurements, the African subjects were familiar with Chinese culture as well as with a higher degree of cultural sensitivity, but the Chinese subjects were unfamiliar with African culture and with a lower degree of cultural sensitivity. Although no previous studies investigated the relationship between the cultural familiarity and consumer ethnocentrism directly, several studies found that tourist's familiarity with the destination can positively affect their local product consumption and their satisfaction about the destination (Seo et al., 2013; Prats et al., 2016; Trianasari et al., 2018). Additionally, a negative relationship between consumer ethnocentrism and cultural sensitivity was found in previous studies, i.e., consumers with a high cultural sensitivity are more positive and feel less threatened by the other culture-ethnic groups, consequently, such consumers prefer imported products more than consumers with a low cultural sensitivity (Wang, 2018). Our study verified the above results by applying the neuroscience method. Specifically, the neural response to the C-logos and A-logos (reflected by N2) of Chinese subjects indicated the existence of consumer ethnocentrism driven by descriptive norms, while the neural reaction of African subjects verified the reduction effect of race-culture familiarity on consumer ethnocentrism.

The results of this study prove that consumer ethnocentrism could exist during the evaluation and selection of brands matched to ethnic groups as well as the origin of the product (local vs. imported), the in-group recommended logos were treated more favorably than the out-group recommended logos in higher ethnocentrism groups (Chinese subject).

One of the limitations of this study is that all the subjects were young male students, future studies, therefore, need to investigate the neural response of the consumer ethnocentrism effect in both male and female subjects of a broader age range. What is more, besides the culture-ethnic grouping basis, future work can investigate consumer ethnocentrism by recruiting subjects from different group categories the individual subjects feel a part of, such as religion (Hornstein, 1972; Fershtman and Gneezy, 2001; Platow and van Knippenberg, 2001; Levine et al., 2005; Stürmer et al., 2006; He et al., 2009; Rand et al., 2009).

This study suggests several implications for locals in addition to international managers and marketers, whereby associating products with a target consumer culture-ethnic group in advertisements, or other marketing activities can benefit from the consumer ethnocentrism effect, leading to higher engagement with their own brands and products.

CONCLUSION

The ERP experiment was conducted to explore the impact of cultural familiarity on the ethnic affiliation of consumer ethnocentrism driven by descriptive norms. The experiment consisted of two stimuli, Asian Chinese and Black African recommenders in the S1 who purchased and recommended headphone brand-logos in S2. The ERP component N2 was enhanced by the in-group recommended logo more than the out-group recommended logos in the Asian Chinese subjects. While no significant difference was found between the two groups of brand-logos in the Black African subjects as a result of cultural familiarity. This research achieves its general aim of studying one of the important issues in international marketing, by examining how consumer ethnocentrism studies can be beneficial in terms of using neuroscience tools such an ERP to supplement the traditional way of using scaled ranges of preferences and questionnaires.

ETHICS STATEMENT

The experiment was conducted at Neuro-management lab, Zhejiang University. All subjects had normal or corrected to normal vision with no history of neurological or psychiatric abnormalities. This study was approved by the Neuromanagement Laboratory Ethics Committee at Zhejiang University. Written informed consent was obtained from all participants before the ERP experiment.

AUTHOR CONTRIBUTIONS

QM conceived the presented idea, verified the analytical methods and supervised the findings of this work. HA and LH carried out the experiment. HA wrote the manuscript with support from QM and LH. All authors discussed the results and contributed to the final manuscript.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fnhum.2019.00220/full#supplementary-material

TABLE S1 | Comprise of seven datasets. (1) The age of the subject. (2) The rating score of S1. (3) The rating score of S2 (the race stimulus, S1 was eliminated). (4) The cultural sensitivity scale score. (5) The mean amplitude of P300 elicited by S1. (6) The mean amplitude of N2 elicited by S2. (7) The rating score of S2 (with S1 in the ERP experiment).

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The Monetary Incentive Delay (MID) Task Induces Changes in Sensory Processing: ERP Evidence

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Numerous cognitive studies have demonstrated experience-induced plasticity in the primary sensory cortex, indicating that repeated decisions could modulate sensory processing. In this context, we investigated whether an auditory version of the monetary incentive delay (MID) task could change the neural processing of the incentive cues that code expected monetary outcomes. To study sensory plasticity, we presented the incentive cues as deviants during oddball sessions recorded before and after training in the two MID task sessions. We found that after 2 days of training in the MID task, incentive cues evoked a larger P3a (compared with the baseline condition), indicating there was an enhancement of the involuntary attention to the stimuli that predict rewards. At the individual level, the training-induced change of mismatch-related negativity was correlated with the amplitude of the feedback-related negativity (FRN) recorded during the first MID task session. Our results show that the MID task evokes plasticity changes in the auditory system associated with better passive discrimination of incentive cues and with enhanced involuntary attention switching towards these cues. Thus, the sensory processing of incentive cues is dynamically modulated by previous outcomes.

Keywords: neuroplasticity, attention, reinforcement learning (RL), feedback-related negativity (FRN), monetary incentive delay task, oddball paradigm, mismatch negativity (MMN), P3a

INTRODUCTION

The traditional decision-making theory assumes that individuals' choices are driven by values that are associated with prospective outcomes. Numerous neurobiological studies have implicated the involvement of dopaminergic neurons in the valuation stage of the decision-making process (Schultz, 2006) and in behavioral adaptations (Bromberg-Martin et al., 2010). Interestingly, popular neurobiological models of decision making (Rangel et al., 2008; Wang, 2012) acknowledge the key role of learning in reward-based decisions, but they indirectly assume that the primary sensory inputs to dopaminergic (decision making) networks are stationary and independent from previous decisions. However, many cognitive studies have demonstrated experience-induced plasticity in the primary sensory cortices (Atienza et al., 2005; Kujala and Näätänen, 2010; Shtyrov et al., 2010; Pantev and Herholz, 2011), indicating that repeated decisions could modulate sensory processing, which, in turn, could modulate follow-up decisions. In the current study, we tested the hypothesis that the repeated associations of a stimulus with a monetary outcome may evoke plasticity in an individual's sensory processing. Furthermore, we tested the link between the neural activity underlying value-based learning and plastic changes in the sensory cortices.

Sensory cortices retain the capacity for experience-dependent changes, or plasticity, throughout life. These changes constitute the mechanism of perceptual learning (Gilbert et al., 2001). Numerous event-related potential (ERP) studies have shown training-induced neuroplastic changes in auditory information processing that could be explained by the reorganization of neuronal networks and changes in the sensitivity to and processing of relevant information (Atienza et al., 2005; Kujala and Näätänen, 2010; Shtyrov et al., 2010; Pantev and Herholz, 2011). In conditioning paradigms, where auditory tones are used as conditioning stimuli, the training results in associative representational plasticity, which selectively facilitates responses to the conditioned stimuli (Weinberger, 2007). According to the representational plasticity theory, the tuning of the neurons in the primary auditory cortex is selectively shifted towards the characteristics of the conditioned stimulus, thus biasing the whole sensory system to emphasize the behaviorally important stimulus (Diamond and Weinberger, 1986; Bakin and Weinberger, 1990; Edeline and Weinberger, 1993; for a review, see Weinberger, 2015).

The plasticity of auditory processing is often reflected in the mismatch negativity (MMN) component of auditory ERPs. The MMN is an electrophysiological signature of a pre-attentive process that detects alterations in a regular sound sequence (Näätänen, 1990; Winkler et al., 1996). The MMN is evoked by a deviant or rare (i.e., oddball) event embedded in a stream of repeated or familiar events (i.e., standards; Näätänen et al., 2007). The MMN is frequently explained in terms of predictive coding, which is a general theory of perceptual inference (Garrido et al., 2009; Carbajal and Malmierca, 2018). According to this theory, the brain actively learns the regularities of the sensory input and models an internal representation of this information. When the model's prediction of the forthcoming stimulus is violated, the mismatch signal is generated (Paavilainen et al., 1999; Näätänen et al., 2005; Winkler, 2007).

Importantly, the amplitude of the MMN is modulated by previous experiences and correlates with behavioral discrimination performance. An initial poor differentiation of the deviant and standard stimuli, as well as inaccurate performance, are correlated with a low-amplitude MMN, while active learning to discriminate deviant stimuli results in larger MMN activity (Sams et al., 1985; Novak et al., 1990; Näätänen et al., 1993; Tiitinen et al., 1994; Cheour et al., 2002). Furthermore, learning-dependent changes of the MMN's amplitude have been demonstrated not only right after discrimination training, but also several days later (Kraus et al., 1995; Tremblay et al., 1998; Menning et al., 2000; Atienza et al., 2002, 2005), a training-dependent long-term effect on pre sensory processing in the auditory cortex. Thus, previous studies have robustly demonstrated that training-induced changes of the MMN amplitude are reliable markers of experience-induced neuroplasticity.

Training-induced enhancement in the MMN is often followed by an increased fronto-central P3a component with a 230–300 ms latency (Draganova et al., 2009). Importantly, P3a, which reflects attentional reorientation to salient, task-irrelevant cues (Escera et al., 1998; Wetzel et al., 2011), is believed to be associated with executive functions (Light et al., 2007; Fjell et al., 2009) and possibly working memory encoding (Bledowski et al., 2004). P3a activity has been linked to both short- and long-term plasticity changes as a result of auditory training (Atienza et al., 2004; Uther et al., 2006; Draganova et al., 2009). Overall, the MMN and P3a components are reliable markers of induced perceptual learning.

We hypothesized that—similar to the effects of classical conditioning—repeated exposure to acoustic incentive cues that predict different monetary outcomes might induce plastic changes in the auditory processing that underlie better discrimination and/or an involuntary attention switch to incentive cues with higher expected values (EVs). Therefore, learning-based neuroplastic changes could be manifested in the increased amplitude of the MMN and/or P3a components. An increased MMN amplitude would indicate a more fine-grained discrimination of the auditory cues, whereas an increased P3a would indicate a stronger reallocation of attention to the cues guided by the prefrontal cortex.

The monetary incentive delay (MID) task is a popular tool for studying the different stages of reward-based learning, from reward anticipation to its delivery (Knutson et al., 2000, 2005). In the traditional version of the MID task, visual stimuli, such as circles, squares, and triangles, are utilized as incentive cues that code the probabilities and magnitudes of outcomes. The MID task allows the manipulation of the EVs, the sum of all possible outcomes of a particular choice multiplied by their probabilities, and reward-prediction errors (RPEs). The modern theory of reinforcement learning (RL) assumes that RPE signals drive the feedback-guided adaptive modification of behavior to environmental change (Sutton and Barto, 1998). In the current study, we investigated the link between neural activity correlated to RPE signals and neural activity correlated to neuroplasticity (MMN and P3a).

To study auditory perceptual learning, we developed an auditory version of the MID task (Krugliakova et al., 2018) where the sounds of different frequencies and intensities were used as incentive cues for signaling the prospective gain's probabilities and magnitudes. We suggested that a continuous MID task could evoke plastic changes in auditory processing such that processing the incentive cues would be facilitated proportionally to the cues' EVs. To test this hypothesis, we analyzed feedback-related activity during the MID task. Numerous electroencephalography (EEG) studies have shown that the feedback-related negativity (FRN) component reflects a neural activity that underlies learning and performance monitoring

(Holroyd and Coles, 2002; Montague and Berns, 2002; Montague et al., 2004; van Meel et al., 2005; Sambrook and Goslin, 2016). The FRN is a negative deflection with a fronto-central maximum occurring 240–340 ms after receiving negative feedback. According to Holroyd and Coles (2002), the FRN reflects a phasic decrease in dopaminergic activity that disinhibits the anterior cingulate cortex, which signals an RPE (Hajihosseini and Holroyd, 2013). A number of studies have provided evidence for the links between the FRN and mid-frontal theta oscillations with individual behavioral changes (for a review, see Luft, 2014). We recorded the FRN during the MID task and then studied the correlation of the FRN's amplitude with changes in the MMN and P3a, which was recorded using the oddball paradigm before and after the MID task. Overall, we tested two hypotheses: (I) MID task performance can induce plastic changes in the auditory system as reflected in MMN and P3a amplitude; and (II) individual differences in the plastic changes of the auditory processing can be predicted by the individual differences of the FRN recorded during the MID task. Overall, our findings could clarify a relationship between reward-based learning and sensory plasticity during behavioral adaptations.

MATERIALS AND METHODS

Subjects

Forty-two subjects (17 females) participated in an EEG experiment in which both behavioral and electrophysiological data were collected. Five subjects were excluded from the analysis because of excessive EEG artifacts or too few artifact-free trials (less than 20 trials per trial type; for the same approach, see Marco-Pallares et al., 2011). Data of 37 subjects (15 females, 23 ± 3 years old) were included in the final statistical analysis. All of the subjects were right-handed with normal or corrected-to-normal vision and reported normal hearing; they did not report any history of psychiatric or neurological problems. The experiment was carried out in accordance with the recommendations of the Declaration of Helsinki and its amendments, and the protocol was approved by the ethics committee of the National Research University Higher School of Economics. All subjects gave written informed consent in accordance with the Declaration of Helsinki.

Study Design

The primary goal of the current study was to investigate the effects of a continuous MID task requiring the anticipation and processing of rewards on the neural processing of auditory incentive cues (see **Table 1**). For this purpose, we designed an experiment consisting of two tasks (the MID task and oddball paradigm) that was presented on two successive days (**Figure 1**). The rationale to use two MID-task sessions in two subsequent days was that including at least one full night of sleep following the initial acquisition could be beneficial for the individual's associative leaning (Atienza et al., 2004; Gottselig et al., 2004b; Talamini et al., 2008; Ramadan et al., 2009). The results of both MID-task sessions were included to test which stage of the training would be more crucial for the learning-induced changes in sensory processing: the initial phase of training that can contribute to the overnight memory consolidation or the final phase preceding the retest in the oddball task.

Experimental Procedure

Prior to the experiment, the participants were informed that during each of the two MID task sessions, they had a chance to earn some amount of money and that at the end of the second day, they would receive the largest of the two total gains.

Day 1

At the beginning of each experiment, the ability of participants to discriminate between four auditory stimuli was tested during an identification test. Next, the participants performed the first session of a passive oddball task where the four above-mentioned auditory stimuli were used as deviant stimuli.

At the beginning of the MID task, the participants were instructed about the meaning of each auditory stimuli as an "acoustic cue" that coded a specific EV. Finally, the participants performed the first session of the MID task where four auditory stimuli were used as incentive cues with different EVs.

Day 2

At approximately the same time of the day, the participants performed the MID task and the oddball task for the second time. Both the MID and the oddball tasks were analogous across the two experimental days. At the end of the second day, the subjects were informed of the monetary gain on the first and the second day and were given the exact amount of the largest gain. The duration of the studies, including the preparation time, was 2 h on the first experimental day and 1.5 h on the second day (**Figure 1A**).

Identification Test

The identification test was designed to ensure that the participants were sufficiently good at discriminating among auditory stimuli that were later used as incentive cues during the MID task. As shown in the previous studies of auditory discriminative training, the training-evoked changes in the MMN could be observed only if subjects could initially discriminate among the various tones relatively well (Gottselig et al., 2004a). The participants were instructed to press a button corresponding to the delivered sound. The sound descriptions and target buttons were displayed on the screen during the task. The participants received positive and negative visual feedback to facilitate learning. The EEG session started when a subject successfully identified 8 out of 10 consecutive sounds. On average, the participants made more mistakes in frequency identification (4.08 ± 0.80; the mean ± the standard error of the mean) than in intensity identification (1.78 ± 0.36) and in simultaneous frequency and intensity identification (1.35 ± 0.39).

Auditory MID Task

During the auditory MID task (**Figure 1B**), the participants were exposed to acoustic cues that encoded the prospective gain magnitude [4 or 20 Russian rubles (RUB) ≈ 0.06 or 0.20 USD] and the probability of a win ($p = 0.80$ or $p = 0.20$). After a variable anticipatory delay period (2,000–2,500 ms), the participants responded with a single button press immediately after the

TABLE 1 | Acoustic stimuli in the oddball task and monetary incentive delay (MID) task.

Stimuli	Oddball task	MID task	
		Group 1	Group 2
Std	(523 Hz)/70 dB	-	-
Dev_{I1F1}	−10/8 semitones (487 Hz)/55 dB	+20 RUB/0.80	+20 RUB/0.20
Dev_{I1F2}	+10/8 semitones (562 Hz)/55 dB	+4 RUB/0.80	+20 RUB/0.80
Dev_{I2F1}	−10/8 semitones (487 Hz)/80 dB	+20 RUB/0.20	+4 RUB/0.20
Dev_{I2F2}	+10/8 semitones (562 Hz)/80 dB	+4 RUB/0.20	+4 RUB/0.80

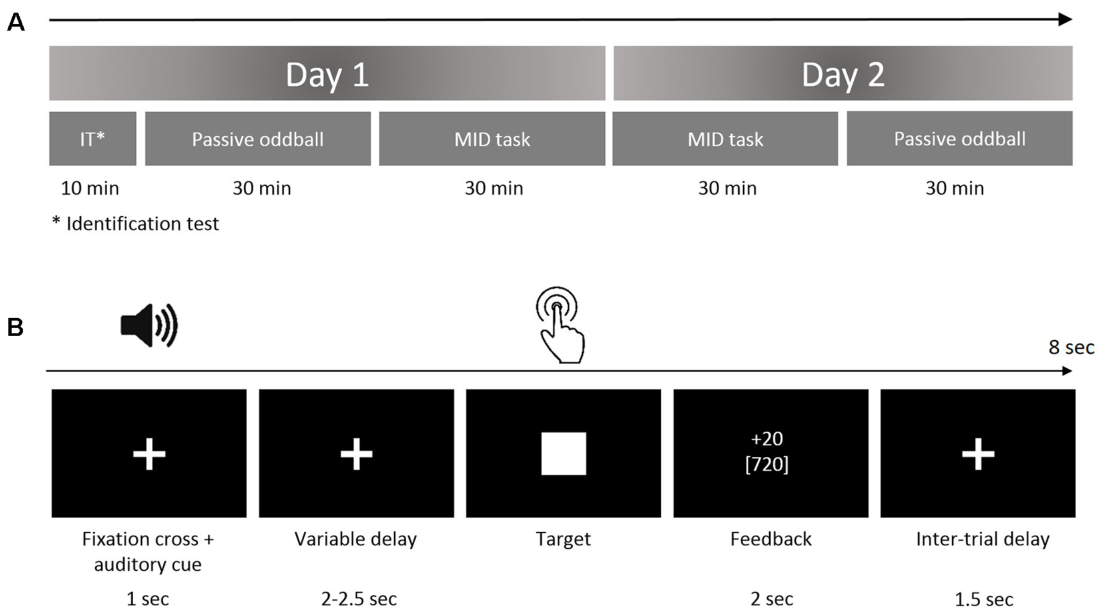

FIGURE 1 | **(A)** Study protocol. The subjects performed the oddball task and monetary incentive delay (MID) task on two successive days. The identification test prior to the first oddball session was designed to ensure that the participants could discriminate among the auditory stimuli. **(B)** The structure of the trial in the auditory version of the MID task. In the beginning of each trial (first box), the participants were exposed to acoustic cues encoding the prospective gain magnitude [4 or 20 Russian rubles (RUB)] and the probability of a win (p = 0.80 or p = 0.20). After a variable anticipatory delay period (second box, fixation cross, duration = 2,000–2,500 ms), the participants responded with a single button press as quickly as possible after the presentation of a visual target (third box, white target square). Next, 800 ms after the button press (the end of each trial), a feedback screen (fourth box, duration = 2,000 ms) was presented. During the feedback, the top number indicated the amount of money won during that trial, and the bottom number indicated the participant's total amount won. The overall duration of a single trial was 8 s on average.

presentation of a visual target (white square, see **Figure 1B**). Next, the feedback (duration = 2,000 ms, delay = 800 ms) notified the participants whether they had won or missed money during that trial and showed their cumulative total. The 800-ms delay before the feedback was aimed at eliminating the effects of the visual target on feedback-locked ERPs. The overall duration of a single trial was ∼8 s. The probability of a win was manipulated by altering the average target duration through an adaptive timing algorithm that followed the subjects' performance such that they would succeed in ∼80% of the high-probability trials and in ∼20% of the low-probability trials (Knutson et al., 2005). Positive outcomes occurred in an average of 58 ± 6 trials out of 76 high-probability trials and an average of 14 ± 3 trials out of 76 low-probability trials.

To encode prospective reward probability and magnitude, the auditory cues had two levels of frequency and two levels of intensity. The probability and magnitude of the reward were encoded differently in two experimental groups. In Group 1 (n = 19), the intensity of the acoustic cue encoded the gain's magnitude, while the frequency encoded the gain probability. In Group 2 (n = 18), the encoding of the gain magnitude and gain probability was reversed. To eliminate the effects of the stimuli's physical parameters on the ERPs, we polled the data of the two experimental groups.

Auditory Stimuli and Oddball Paradigm

To probe the learning-related neuroplasticity of the auditory processing, the subjects participated in two identical passive oddball tasks, with the first session of the oddball task performed on Day 1 before the first MID session, while the second session of the oddball task was performed after the second MID session on Day 2 (**Figure 1A**). The standard stimuli in the oddball paradigm were composed of three sinusoidal partials (523, 1,046, and 1,569 Hz, with a fundamental frequency corresponding to C5 of the Western musical scale, intensity = 70 dB). Four distinct deviant tones (**Table 1**) differed from the standard tone in both frequency and intensity such that the probability of an increment or decrement was even. The deviants differed from the standards in their frequency by +10/8 and −10/8 semitones on the Western musical scale (fundamental frequencies 562 Hz for the higher and 487 Hz for lower deviant tones). The intensity of the deviants was either smaller or larger than the standard (70 dB) by 15 dB and 10 dB, respectively (55 dB and 80 dB). All stimuli lasted 200 ms (including 5 ms rising and falling times). The stimuli were generated with Praat acoustics software (Boersma, 2001).

Importantly, the same four deviant oddball stimuli were also used as acoustic reward-predictive cues for the auditory MID task. The acoustic cues signaled high or low prospective reward probabilities (0.80 and 0.20, correspondingly) and high or low prospective reward magnitudes (4 or 20 RUB, correspondingly), as illustrated in **Figure 1B**. For example, in Group 1, the deviant stimulus Dev_{I1F1} (487 Hz/55dB) signaled an opportunity to receive 20 RUB with a 0.80 probability (see the details of the reward-predictive cues in **Table 1**).

During the oddball tasks, infrequent deviant stimuli were pseudo-randomly interspersed with a standard stimulus presented with a probability (P_{std}) of 0.80 and with an 800 ± 100 ms onset asynchrony. Each deviant type (Dev_{I1F1}, Dev_{I1F2}, Dev_{I2F1}, and Dev_{I2F2}) was presented as every fourth, fifth, or sixth tone with the same probability (P_{dev} = 0.20/4 = 0.05). Two successive deviants were always of a different type (an example of the progression of tones during a session is as follows: Dev_{I2F2} – Std – Std – Std – Dev_{I1F1} – Std – Std – Std – Std – Std – Dev_{I2F1} – Std – Std – Std – Std – Dev_{I1f1} – Std –. . .). Overall, each oddball session consisted of 2,400 tones (session duration = 30 min), and each of the four deviant stimuli was presented 120 times. Each session started with a training session of four standard stimuli. During passive oddball sessions, the subjects read a book of their own choice.

EEG Data Acquisition

EEG data were recorded with 28 active electrodes (Brain Products GmbH, Gilching, Germany) according to the extended version of the 10-20 system: Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T7, T8, P7, P8, Fz, Cz, Pz, Oz, FC1, FC2, CP1, CP2, FC5, FC6, CP5, and CP6. The active channels were referenced against the mean of two mastoid electrodes to display the maximal MMN and FRN response at the frontal electrode sites. The electro-oculogram was recorded with electrodes placed on the outer canthi and below the right eye. Data were acquired with a BrainVision actiCHamp amplifier (Brain Products GmbH, Gilching, Germany) and sampled at 500 Hz. Impedance was confirmed to be less than 5 kΩ in all electrodes prior to recording.

EEG Data Analysis

EEG signals were preprocessed with BrainVision Analyzer 2.1 (Brain Products GmbH, Gilching, Germany). The EEG was filtered offline (passband 1–30 Hz, notch filter 50 Hz), and then, an independent component analysis (ICA)-based ocular artifact correction was performed. After a manual inspection of the raw data for the remaining artifacts, the data were segmented into epochs of 600 ms and a 100-ms prestimulus epoch. Each trial was baseline corrected to an average activity between −100 and 0 ms before stimulus onset. Epochs, including voltage changes exceeding 75 μV at any channel, were omitted from the averaging. For the oddball task and MID task, the epochs were averaged for two sessions separately. The time windows chosen for the statistical analysis of the ERP components were based on a visual inspection of the grand-average waveforms and previous studies. The ERP components were defined either as the local maximum (P3a) or local minimum (MMN and FRN) of the difference waveform. Once a peak was identified, the amplitude over a ±10-ms window around this peak was averaged individually and then averaged across the participants. We complemented this analysis with the measurement of the area under the ERP curve (AUC, μV *ms), which provides a more precise measure of the overall magnitude of the brain's response (Kappenman and Luck, 2012) in cases of the multipeak nature of the ERP components. The AUC was computed as the approximate integral using the Matlab function *trapz.m*.

All statistical analyses were performed using Matlab 2015a and SPSS software package (22.0).

Analysis of the MMN and P3a Components Recorded During the Oddball Task

To study experience-induced plastic changes, we analyzed the MMN and P3a components before and after the MID task training. The data were segmented for five types of trials: standard stimulus and four types of deviants (Dev_{I1F1}, Dev_{I1F2}, Dev_{I2F1}, and Dev_{I2F2}). The difference waveforms were derived by subtracting the averaged response to the standard stimulus from the averaged response to each type of deviant stimulus. The MMN peak amplitude was identified as the most negative peak in the difference response occurring at 80–250 ms poststimulus onset at the Fz electrode (Näätänen et al., 2007). The P3a peak amplitude was identified as the most positive peak of the difference curve occurring at 180–300 ms poststimulus onset at the same electrode (Seppänen et al., 2012).

For the oddball task, three-factor repeated measures analyses of variance (ANOVAs) with *session* (session 1 vs. session 2), *probability* (low probability vs. high probability), and *magnitude* (small magnitude vs. big magnitude) as the within-subject variables were conducted separately for the MMN and P3a amplitudes. We used the Greenhouse–Geisser correction to estimate the p values. The level of significance was set to $p < 0.05$.

Interaction of FRN With MNN and P3a

We analyzed whether the changes in the MMN and the P3a (between session 1 and session 2) induced by the MID task varied as a function of the FRN amplitude registered during the MID task session 1 and session 2 (FRN1 and FRN2). First, to calculate the *difference MMN*, or dMMN, and the *difference P3a*, or dP3a, we subtracted the difference waveforms in session 1 from the difference waveforms in session 2 (red lines in **Figure 2A**)

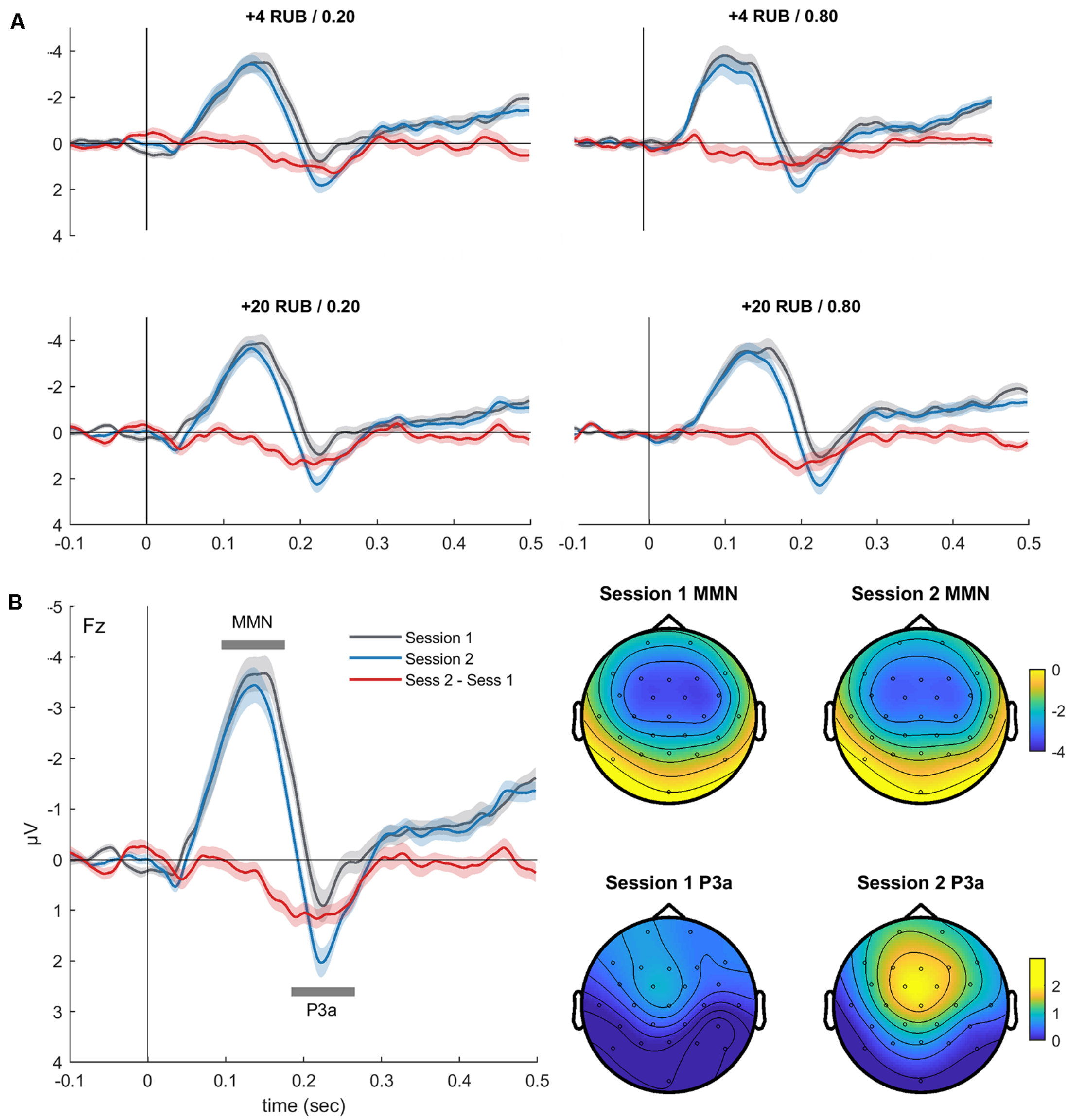

FIGURE 2 | (A) Grand-averaged difference waveforms (Fz, deviant minus standard) superimposed for the two oddball sessions before and after the MID task. The event-related potentials (ERPs) are presented for all four deviants, which also signaled combinations of the magnitude and probability of gain in the MID task. **(B)** Difference waveforms (Fz, left) derived by averaging the ERPs across four conditions, and corresponding scalp topography (right) of the mismatch negativity (MMN) and P3a during oddball sessions 1 and 2. Shaded area around curves represents standard error of the mean (SEM). The topographic maps indicate the voltage distribution of the mean amplitude in the 110–130-ms (MMN) and 220–240-ms (P3a) time windows.

and calculated the average amplitudes of the dMMN (Fz, 50–200-ms time window) and dP3a (Fz, 150–280-ms time window). Second, we calculated a standard FRN separately for both the MID task sessions by subtracting the ERPs of all the positive outcomes from the ERPs of all the negative outcomes (omission of gain). The amplitudes of the FRN (Cz) were quantified within a 230–350-ms time window poststimulus onset. Finally, to measure the relationship between the dMMN and dP3a (oddball task) and the FRN (MID task session 1 and session 2), we calculated the Spearman correlations between these two classes of variables. We used Cook's distance to identify any outliers. Cases with Cook's distances bigger than $4/n$ were excluded from further analysis (Bollen and Jackman, 1985).

RESULTS

Training-Induced Neuroplasticity: Comparison of ERPs in Oddball Sessions 1 and 2

Figure 2A shows the auditory difference waveforms that were calculated separately for sessions 1 and 2 of the oddball task.

The difference waveforms were calculated by subtracting the ERPs of each deviant (Dev_{I1F1}, Dev_{I1F2}, Dev_{I2F1}, or Dev_{I2F2}) from the ERPs of the standard stimuli. Importantly, these four deviants also signaled different rewards during the MID task performed between the two sessions of the oddball task. A negative deflection (MMN) peaking around 120 ms after stimulus onset and a positive deflection (P3a) peaking around 230 ms are distinctly observed in all fronto-central difference waveforms. The latencies and fronto-central distribution clearly indicate the neural generators of the MMN and P3a.

The three-way ANOVA yielded a main effect of the *session* variable for the MMN amplitude ($F_{(1,36)} = 5.80$, $p = 0.02$, $\eta_p^2 = 0.14$), indicating a slight reduction of the MMN in session 2 (-3.98 ± 0.34 μV) compared with session 1 (-4.40 ± 0.34 μV). The main effect of the *session* variable was also significant for the P3a amplitude ($F_{(1,36)} = 29.23$, $p < 0.001$, $\eta_p^2 = 0.45$), reflecting increased P3a in session 2 (2.16 ± 0.24 μV) compared with session 1 (1.31 ± 0.25 μV). The main effects of the *magnitude* and *probability* variables were not significant for both the MMN and P3a amplitudes. No significant interactions between the factors were observed. Thus, only the P3a component showed an increased amplitude in session 2 compared with session 1, which may indicate learning-related plastic changes in the auditory system.

Figure 2A illustrates the similarity of the difference waves' learning-related changes for all deviants. Therefore, for further analysis, we pooled together the difference waveforms obtained for the four types of deviants (**Figure 2B**). Interestingly, we observed a significant reduction of the MMN AUC on the second day ($t_{(35)} = 2.87$, $p = 0.007$), reflecting shorter latency and a smaller duration of the MMN.

To investigate whether such a decrease can be explained by the presentation of repetitive stimulus, we analyzed the changes of the ERPs to oddball standards across two sessions. Notably, we found no changes in the amplitude of the ERPs to standard sound on the second day (**Supplementary Figure S1**). In addition, an analysis of the ERPs to the oddball deviants (without subtracting the standards) demonstrated that on the second day, there was a clear decrease of N200 amplitude that was associated with an enlargement of P300 (all $p < 0.05$). This effect might partially explain the "shortening" of MMN on the second day (**Supplementary Figure S1**). Overall, the MID task, rather than just exposure to sounds during the oddball task, induced changes of the ERPs to auditory monetary cues.

Relationship of RL Signals and Neuroplasticity: Correlation Analysis

As expected, omission of a gain during the MID task evoked the FRN component (**Figures 3A,B**). In both MID task sessions, the FRN appeared as a negative difference wave, with a maximum between 200 and 400 ms following the feedback onset. We did not observe any difference in the FRN amplitude across the two sessions of the MID task: $t_{(36)} = 0.01$, $p = 0.99$ (**Figure 3C**). Furthermore, we found no significant difference in the FRN, AUC across the two sessions: $t_{(36)} = 0.35$, $p = 0.72$. The detailed analysis of the effect of probability, magnitude and valence of the outcome on the FRN amplitude can be found in Krugliakova et al. (2018). To sum it up, the FRN was modulated by all three factors. Although the effect of the probability was significant only for the gain trials, the effect of the magnitude was significant for both the gain and omission of the gain trials.

We tested our hypothesis that individual differences in auditory plasticity reflected in the dMMN and dP3a amplitudes can be predicted by individual differences in the FRN recorded during the MID task sessions (FRN1 and FRN2; **Figure 4**). The correlation analysis yielded a significant relationship between the dMMN and FRN1 ($R_S = 0.50$, $p = 0.02$, FDR corrected), indicating that a larger dMMN was associated with a larger FRN during the MID tasks on the first day. Neither the dP3a and FRN nor the dMMN and FRN2 amplitudes were significantly correlated ($p > 0.70$, FDR corrected). Overall, our results show that plastic changes in the auditory processing correlated with the RL signals recorded during the first MID task training session but not during the second one.

In addition, we tested if the individual differences of the dMMN could be explained by the degree of a subject's involvement in the MID task. To do this, we performed an exploratory analysis of the reaction times (RTs) in trials with different outcome probabilities. Because the probability of a gain was manipulated by altering the average target duration by an adaptive timing algorithm, we suggested that the subjects who paid attention to the incentive cues would react to the white target square faster in low-probability trials when compared with the high-probability trials. Thus, the subjects' involvement in the MID task could be indexed by the difference in the RTs in trials with different outcome probabilities. Therefore, we calculated the dRT: the RTs in trials with low-probability outcomes *minus* the RTs in trials with high-probability outcomes, normalized by the average RTs (a more detailed analysis of the behavioral data of this dataset was published in Krugliakova et al., 2018). We quantified the correlation among the dMMN, P3a, and dRT and observed a positive correlation between the dMMN and dRT ($R_S = 0.39$, $p = 0.02$) but none between the dP3a and dRT ($R_S = -0.07$, $p > 0.7$; **Supplementary Figure S2**). Thus, subjects who showed a larger increase of the MMN amplitude in session 2 relative to session 1 showed a larger difference in their RTs in the trials with different outcomes probabilities. Therefore, the individual differences of the dMMN could be partially explained by the attention that the subjects paid to the incentive cues during the MID task.

DISCUSSION

In the current study, we investigated whether intensive training in the MID task-induced plasticity in sensory processing. As a result, we identified a significant training-induced increase of the P3a component associated with the processing of incentive cues but not of the MMN component. A more detailed analysis of the individual differences demonstrated a large variability in training-induced changes to the MMN. Interestingly, we found a significant correlation between the individual differences in the training-induced changes to the MMN and the individual differences in the FRN, which is a neural marker of the RL elicited during the MID task.

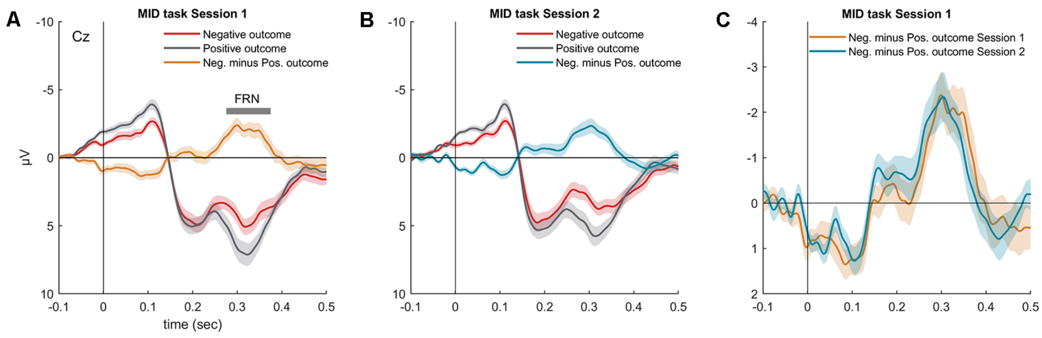

FIGURE 3 | Grand-averaged visual ERP waveforms (Cz) superimposed for the outcomes with different valences (negative outcome, positive outcome) and the difference waveform recorded during the MID task **(A)** session 1 and **(B)** session 2. **(C)** Superimposed difference waveform (Cz, negative minus positive outcomes) for two sessions of the MID task. Shaded area around curves represents SEM.

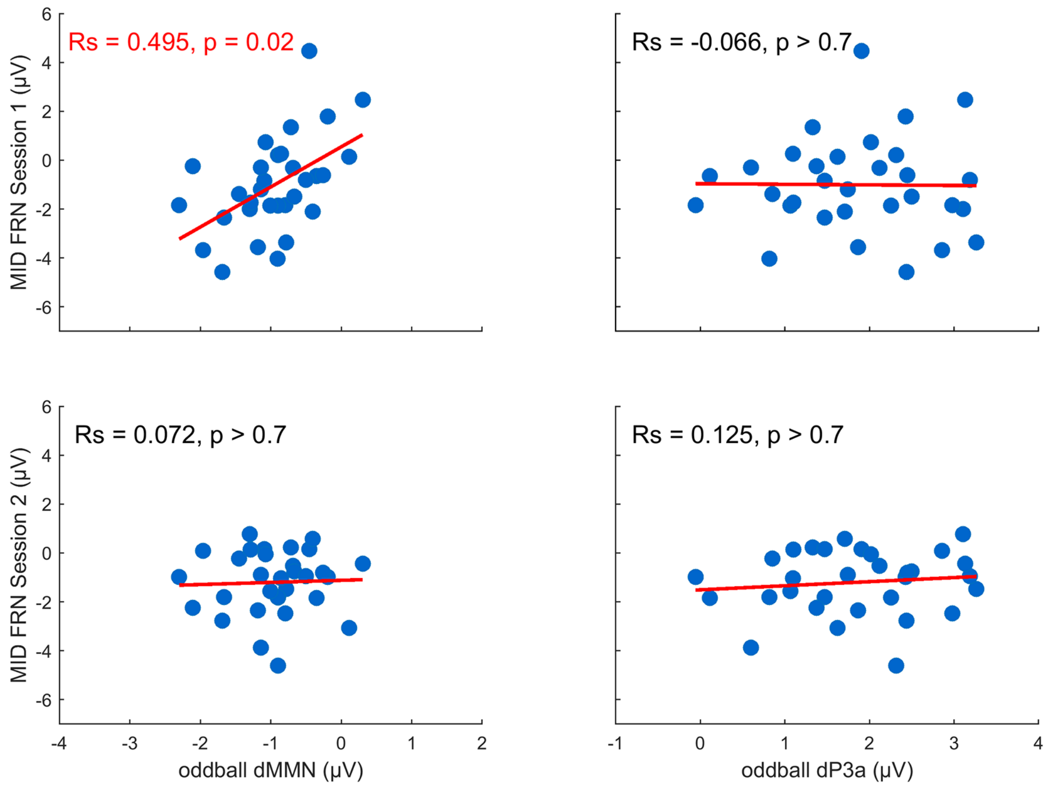

FIGURE 4 | Training-related changes in the MMN and P3a amplitude as a function of the feedback-related negativity (FRN) recorded in the first and the second MID task sessions (the *p*-values were FDR-corrected).

Contrary to our prior hypothesis regarding the increase of the MMN amplitude as a function of training-induced plasticity, in the present study, the MMN decreased on average after two sessions of the MID task. Many studies have shown an increase in the MMN during training (e.g., Atienza et al., 2004; Gottselig et al., 2004a,b). However, a few recent studies have shown that the MMN amplitude could decrease after training (Müller et al., 2002; Perez et al., 2017). In other studies where significant reductions in sensory ERPs after training have been observed (Berry et al., 2010; Miyakoshi et al., 2012), the authors of these articles explained the MMN decrease as being a result of neural adaptation. In addition, a few previous experiments demonstrated an attentional modulation of the MMN (Woldorff et al., 1991; Sussman et al., 2014; Auksztulewicz and Friston, 2015) and the importance of stimulus significance in sensory processing (Bradley, 2009). In light of this, we hypothesized that the direction of the MMN changes could be associated with a different level of the subjects' motivation to distinguish among the different auditory cues during the MID task. Indeed, individual differences of the dMMN in the oddball task could partially account for the individual differences in the RTs during the performance of the MID task across the trials that had different outcome probabilities. In the MID task, the subjects who showed a larger MMN in session 2 than in session 1 of the oddball task responded faster in the trials with a low outcome probability than in the trials with a high outcome probability. Therefore, we speculate that an MMN decrease in session 2 compared with in session 1 might be associated with the decreased attention of the subjects to the auditory cues during MID task performance, which could result in habituation and neural adaptation to auditory stimuli. It should be noted, however, that the observed decrease in the MMN amplitude could be at least partially driven by changes in a stimulus-specific N100 response in addition to changes in the "pure" MMN component. In future studies, this problem can be tackled by using a roving oddball paradigm, where there are no acoustic differences between the standard and deviant.

Nevertheless, we found a link between training-induced changes of the MMN and FRN recorded during the first session of the MID task. Previous studies have demonstrated that the size of the FRN predicted the effectiveness of the learning (for a review, see Luft, 2014). Most of these studies used paradigms that required learning probabilistic associations rather than error-based learning (Yasuda et al., 2004; Frank et al., 2005; Cohen and Ranganath, 2007; Philiastides et al., 2010; van der Helden et al., 2010; Arbel et al., 2013; for a review, see Luft, 2014). In the current study, the FRN recorded during the first session of the MID task correlated with the training-induced changes of the MMN evoked by incentive cues during the oddball task. This indicates that the participants who demonstrated a larger FRN during the first session of the MID task may also have demonstrated an increased MMN, while the participants with smaller FRNs would show a decreased MMN. The training-induced increase of the MMN in subjects with a pronounced FRN might indicate a selectively induced plasticity of the auditory cortex driven by performance in the MID task. Interestingly, the FRN recorded during the first MID session predicted subsequent changes in the MMN amplitude better than the FRN recorded immediately prior to the second oddball session. One possible explanation for this is that the first MID task session was followed by a sufficient amount of time for effective top-down modulation of auditory processing, which, as has been shown, also benefits from sleep (Atienza and Cantero, 2001; Atienza et al., 2004).

Contrary to our expectations, the decrease in the MMN amplitude was not specific to low EVs. This insensitivity of the MMN's changes to manipulations of the EVs could be explained by limitations of the standard MID task. According to the auditory version of the MID task, all cues should be equally important for optimal performance in the task. In other words, to react specifically to one of the incentive cues, one would need to discriminate this cue from all other incentive cues. Thus, the participants should learn all of the cues equally well, regardless of their EVs. This interpretation would be in accordance with the predictions of the reverse hierarchy theory of perceptual learning (Ahissar et al., 2009): for perceptual learning to occur, specific learning paradigms that are optimal for the modification of sensory representations and that result in more accurate perceptions need to be utilized. Unfortunately, the standard MID task is neither designed to test the effects of perceptual learning as training-induced improvements in discrimination nor the controls for sensitization as a nonspecific facilitation of stimuli identification. To further study the effects of reward-based learning on sensory plasticity, a modification of the MID task would be necessary, for example, better discrimination of incentive cues with higher EVs being relevant for task performance.

Learning-related changes to the MMN are frequently accompanied by changes to the P3a. The MMN has been linked to the perceptual processes underlying stimulus discrimination, and it is often used as an index of central auditory system plasticity (for a review, see Näätänen et al., 2007), whereas the P3a manifests the allocation of involuntary attention to the relevant stimuli (Polley, 2006). For example, learning foreign-language phonemes evokes correlated MMN-P3a changes (Shestakova et al., 2003). In a recent review, Jääskeläinen et al. (2011) proposed a model in which rapid plasticity can support not only sensory and short-term memory, but also selective and involuntary attention and perceptual learning, depending on the input type (bottom-up vs. top-down). Recent results of human experimental studies fit this model well. For example, Seppänen et al. (2012, 2013) compared the short-term plasticity effect on involuntary attention using the P3a component of ERPs between musicians and nonmusicians. During passive exposure to sounds after an active discrimination session, the musicians showed a habituation of the P3a, while nonmusicians showed an enhancement of the P3a between blocks. Corroborating this finding, a number of studies showed congruent dynamic changes in the MMN and P3a, suggesting that the MMN-P3a complex is an index of involuntary attention control (Friedman et al., 1998; Debener et al., 2005; Barry et al., 2016). Interestingly, in the current study, the degree of the amplitude changes of the P3a and MMN were not in line with these previous studies. Unlike the MMN, we observed an increase in the P3a amplitude in the second oddball session across all four types of incentive cues. The P3a result without an MMN effect could be explained by a top-down process that mediated experience-induced plasticity, which, in turn, resulted in the enhanced change detection during the oddball task, as was confirmed in the study by Seppänen et al. (2012).

STUDY LIMITATIONS

There are a number of limitations to the current study that should be noted. First, using the standard MID task, we were not able to address how associative learning affects the sensory processing of stimuli with different incentive values. A single-block design does not allow for assigning different relevance levels to incentive cues, making them equally important for the correct task performance. One way to tackle this problem would be to use a multiple block design where the discrimination of different sounds would be task relevant only for some of the blocks. Second, we did not include a second identification task after the second MID task because we observed sufficient discrimination prior to the first MID task. Thus, in our paradigm, we cannot expect a significant change in the number of mistakes because of the ceiling effect in the accuracy. However, a lack of the measure of the performance changes tempers our interpretation of the link between the EEG markers and potential behavioral benefits. Third, to optimize the auditory ERP data collection during the oddball task, it would be beneficial to use a multi-feature oddball paradigm, such as Optimum-1, allowing an efficient recording of brain responses to several acoustic feature changes within a very short recording time (Näätänen et al., 2004). Finally, 28-channel EEG does not provide a sufficient space resolution for the source reconstruction. Thus, in the current study, the conclusions regarding the localization of the observed effects and involvement of particular brain networks should be regarded with caution.

CONCLUSION

In the current study, we tested whether repeated exposure to the stimuli that signal different incentive values in the MID task changes their sensory processing when tackled in the oddball tasks. In the absence of the group MMN effect, we observed learning-related changes of the P3a, indicating a stronger reallocation of attention to the incentive cues. The correlational analysis of individual MMN amplitudes with the MID-session FRN responses revealed that a stronger RL signal was associated with a more fine-grained discrimination of the incentive cues.

Overall, our results showed that plastic changes associated with better discrimination could be sensitive to the continuing valuation of incentive cues that leads to enhanced involuntary attention switching. Further studies will be needed to investigate whether auditory sensory processing may depend on the history of previous decisions.

ETHICS STATEMENT

The experiment was carried out in accordance with the recommendations of Declaration of Helsinki and its amendments, and the protocol was approved by the ethics committee of the National Research University Higher School of Economics. All subjects gave written informed consent in accordance with the Declaration of Helsinki.

AUTHOR CONTRIBUTIONS

AS, VK, YS and EK designed the experiment. EK, AG and TF recruited subjects, collected and pre-processed the data. EK, AG, TF, VM and AS performed the analysis of the data. EK, AG, YS, VK, VM and AS wrote the article. All authors approved the final version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fnhum.2019.00382/full#supplementary-material.

FIGURE S1 | Grand-averaged auditory ERP waveforms (Fz) for the standard sound and four types of deviants (without standard subtraction) superimposed for two oddball sessions before and after the MID task.

FIGURE S2 | Training-related changes in the MMN and P3a amplitudes as a function of the dRT (difference in reaction time: the RT in low-probability minus the RT in high-probability trials, normalized by the average RT).

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