TEMPORAL DYNAMICS OF REWARD PROCESSING IN HUMANS: FROM ANTICIPATION TO CONSUMMATION

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PUBLISHED IN: Frontiers in Psychology and Frontiers in Neuroscience

frontiers Research Topics

ISSN 1664-8714
ISBN 978-2-88966-074-2
DOI 10.3389/978-2-88966-074-2

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TEMPORAL DYNAMICS OF REWARD PROCESSING IN HUMANS: FROM ANTICIPATION TO CONSUMMATION

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Citation: Zheng, Y., Gu, R., Pfabigan, D. M., eds. (2020). Temporal Dynamics of Reward Processing in Humans: From Anticipation to Consummation. Lausanne: Frontiers Media SA. doi: 10.3389/978-2-88966-074-2

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frontiers in Psychology

EDITORIAL
published: 19 August 2020
doi: 10.3389/fpsyg.2020.01901

Editorial: Temporal Dynamics of Reward Processing in Humans: From Anticipation to Consummation

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Keywords: reward, anticipation, consummation, temporal dynamics, individual differences

Editorial on the Research Topic

Temporal Dynamics of Reward Processing in Humans: From Anticipation to Consummation

People often want what they like, and like what they want. However, this lay knowledge is inconsistent with findings in reward-related disorders (Treadway and Zald, 2011; Whitton et al., 2015; Nusslock and Alloy, 2017). For example, patients suffering from depression and schizophrenia sometimes show intact hedonic responses to pleasurable stimuli, but are less willing to expend effort to acquire rewards (Culbreth et al., 2018). Drug addiction is characterized by an excessive craving for drugs, but is rarely companied by the expected positive hedonic responses (Robinson and Berridge, 1993). Individuals with anorexia-type eating disorders have normal levels of "wanting," but reduced levels of "liking" of foods (Berridge et al., 2010). These clinical observations indicate that reward processing is not a homogenous construct but consists of two mainly successive phases, anticipation and consummation, as it unfolds over time (Rangel et al., 2008; Romer Thomsen et al., 2015). Although the dissociation between reward anticipation and consummation is well-established in seminal animal models (Berridge and Robinson, 2003), more work is needed to disentangle reward anticipation and consumption in humans. The current Research Topic includes 11 original articles portraying the dynamics of reward processing in humans in terms of self-report, behavioral, or neural changes.

In this topic, three articles focus on the role of emotions and personality traits in anticipatory and consummatory phases of reward processing. First, Li X. et al. asked participants to evaluate their daily experience of hedonic feelings by using experience sampling, and found that dysphoric college students reported less state anticipatory and consummatory pleasure compared with their non-dysphoric counterparts. Their results support the view that anhedonia leads to deficits in both anticipatory and consummatory phases of reward processing. Meanwhile, Huang et al. combined the classic Monetary Incentive Delay task (Knutson et al., 2000) with functional magnetic resonance imaging (fMRI) in a sample of adolescents. They discovered that callous-unemotional personality traits were positively correlated with ventral striatum activation in the anticipatory phase, but this effect was dependent on externalizing behavior. In the consummatory phase, externalizing behavior was negatively correlated with amygdala activation during punishment receipt even after controlling for callous-unemotional traits. These results help to clarify the relationship between psychopathic traits and antisocial behavior in dysfunctional reward processing. Finally, Ferreira et al. asked students to place bids to obtain food during fMRI recording and found that chronically stressed participants proposed lower bids than non-stressed ones, but there was no behavioral and neural differences during cognitive regulation of craving.

Edited and reviewed by:
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Specialty section:
This article was submitted to
Decision Neuroscience,
a section of the journal
Frontiers in Psychology

Received: *26 June 2020*
Accepted: *10 July 2020*
Published: *19 August 2020*

Citation:
Zheng Y, Gu R and Pfabigan DM (2020) Editorial: Temporal Dynamics of Reward Processing in Humans: From Anticipation to Consummation. Front. Psychol. 11:1901. doi: 10.3389/fpsyg.2020.01901

Two articles focus on the electrophysiological correlates of option evaluation, a critical stage of reward-based decision-making during which individuals evaluate and assign a value to each available option (valuation). First, Wang et al. examined event-related potential (ERP) responses of probability weight and monetary magnitude during the evaluation of a risky reward. The results showed that probability weight was encoded by the P200, the medial frontal negativity (MFN), and the late positive potential (LPP) components, whereas monetary magnitude was solely encoded by the MFN. The results demonstrated distinct temporal dynamics involved in the processing of probability weight and monetary magnitude. Meanwhile, Zhu et al. investigated both ERP and oscillatory correlates underlying the evaluation of ambiguous options using an ambiguous choice task. The authors found that delta activity was enhanced for low- vs. high-ambiguity options 200–400 ms after option onset, and for high- vs. low-reward options 400–500 ms after option onset. Ambiguity and reward information were integrated during the time window of 500–600 ms as indexed by both the P3 component and delta activity. These results help clarify neural dynamics of ambiguity vs. reward processing during option evaluation.

Four articles in this volume focus on the characteristics of reward processing in terms of its subcomponents as diverse as anticipation, learning, and consummation. Yao et al. applied an emotion (vs. sex) recognition task while participants anticipated either reward or non-reward. Their results showed that reward anticipation facilitated the processing of target information only when the target was defined by the emotional arousal of stimuli. Using a visual search task, Zhou et al. investigated the effects of prior reward learning on the processing of non-target emotional faces and found that reward history had stronger effects on fearful faces than happy faces. These two studies could further our understanding of the interaction of emotions and reward. Wu et al. investigated the impact of working memory capacity on value-driven attentional capture of reward history, and found that under the memory load condition, attentional capture of target information was more likely to be distracted by low reward-value distractors. By assessing ERPs, Yu et al. were interested in how arbitrary group membership affects the processing of reward and loss feedback in a male sample. Contrary to their expectations, the authors observed no direct support for increased in-group bias in their gambling observation task. ERP results showed that their participants employed more attentional resources during outcome processing of out-group individuals. This suggests an enhanced need for perspective taking in these cases.

Adopting a more clinically-oriented perspective, Li Q. et al. used structural equation analysis to characterize gender differences in regards to how impulsivity, coping styles, and Behavioral Inhibition/Approach System (BIS/BAS) influence internet addition in adolescents. Emotion-focused coping mediated the relationships between impulsivity/internet addition and BIS/internet addiction in girls, while problem-focused coping strategies were mostly observed to mediate the relationships between impulsivity/internet addiction and BAS/internet addiction in boys. These findings suggest that gender-sensitive training approaches should be devised to target internet addiction in adolescents more appropriately. Based on the observation that individuals undergoing evaluation of traumatic brain injury may be malingering neurocognitive deficits for compensatory benefits, Neal et al. developed a novel neural-based method for discriminating fake (i.e., simulated) from true brain injury. The authors found that individuals simulating memory deficits were characterized by delayed left frontal neural responses during recognition of studied items, which reached sensitivity of 80% and specificity of 79% in differentiating malingered from true brain injury.

In sum, the experimental findings presented in this topic shed light on the temporal dynamics (anticipation vs. consummation) of reward processing and indicate a possibility of further decomposing reward anticipation/consummation into subcomponents with distinct theoretical significance. Future research should extend existing theoretical models of reward processing by better characterizing implicated sub-processes such as stimulus-reward associations, effort computations, feedback integration, and social context effects. By addressing these issues, we may better inform more targeted prevention of and interventions for reward-related disorders.

AUTHOR CONTRIBUTIONS

YZ conceived the idea of the Research Topic. YZ, RG, and DP have made a substantial, direct and intellectual contribution during preparation of the editorials, and approved it for publication.

FUNDING

This work was supported by the National Natural Science Foundation of China (31971027, 31571161, and 31671173).

REFERENCES

Berridge, K. C., Ho, C. Y., Richard, J. M., and DiFeliceantonio, A. G. (2010). The tempted brain eats: pleasure and desire circuits in obesity and eating disorders. *Brain Res.* 1350, 43–64. doi: 10.1016/j.brainres.2010.04.003

Berridge, K. C., and Robinson, T. E. (2003). Parsing reward. *Trends Neurosci.* 26, 507–513. doi: 10.1016/S0166-2236(03)00233-9

Culbreth, A. J., Moran, E. K., and Barch, D. M. (2018). Effort-cost decision-making in psychosis and depression: could a similar behavioral deficit arise from disparate psychological and neural mechanisms? *Psychol. Med.* 48, 889–904. doi: 10.1017/S0033291717002525

Knutson, B., Westdorp, A., Kaiser, E., and Hommer, D. (2000). FMRI visualization of brain activity during a monetary incentive delay task. *Neuroimage* 12, 20–27. doi: 10.1006/nimg.2000.0593

Nusslock, R., and Alloy, L. B. (2017). Reward processing and mood-related symptoms: an RDoC and translational neuroscience perspective. *J. Affect. Disord.* 216, 3–16. doi: 10.1016/j.jad.2017.02.001

Rangel, A., Camerer, C., and Montague, P. R. (2008). A framework for studying the neurobiology of value-based decision making. *Nat. Rev. Neurosci.* 9, 545–556. doi: 10.1038/nrn2357

Robinson, T. E., and Berridge, K. C. (1993). The neural basis of drug craving: an incentive-sensitization theory of addiction. *Brain Res.* 18, 247–291. doi: 10.1016/0165-0173(93)90013-P

Romer Thomsen, K., Whybrow, P. C., and Kringelbach, M. L. (2015). Reconceptualizing anhedonia: novel perspectives on balancing the pleasure networks in the human brain. *Front. Behav. Neurosci.* 9:49. doi: 10.3389/fnbeh.2015.00049

Treadway, M. T., and Zald, D. H. (2011). Reconsidering anhedonia in depression: lessons from translational neuroscience. *Neurosci. Biobehav. Rev.* 35, 537–555. doi: 10.1016/j.neubiorev.2010.06.006

Whitton, A. E., Treadway, M. T., and Pizzagalli, D. A. (2015). Reward processing dysfunction in major depression, bipolar disorder and schizophrenia. *Curr. Opin. Psychiatry* 28, 7–12. doi: 10.1097/YCO.0000000000000122

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Psychology

ORIGINAL RESEARCH
published: 26 March 2019
doi: 10.3389/fpsyg.2019.00554

Neural Dynamics of Processing Probability Weight and Monetary Magnitude in the Evaluation of a Risky Reward

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OPEN ACCESS

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Specialty section:
This article was submitted to
Decision Neuroscience,
a section of the journal
Frontiers in Psychology

Received: *14 January 2019*
Accepted: *27 February 2019*
Published: *26 March 2019*

Citation:
Wang G, Li J, Wang P, Zhu C, Pan J and Li S (2019) Neural Dynamics of Processing Probability Weight and Monetary Magnitude in the Evaluation of a Risky Reward.
Front. Psychol. 10:554.
doi: 10.3389/fpsyg.2019.00554

Risky decision-making involves risky reward valuation, choice, and feedback processes. However, the temporal dynamics of risky reward processing are not well understood. Using event-related brain potential, we investigated the neural correlates of probability weight and money magnitude in the evaluation of a risky reward. In this study, each risky choice consisted of two risky options, which were presented serially to separate decision-making and option evaluation processes. The early P200 component reflected the process of probability weight, not money magnitude. The medial frontal negativity (MFN) reflected both probability weight and money magnitude processes. The late positive potential (LPP) only reflected the process of probability weight. These results demonstrate distinct temporal dynamics for probability weight and money magnitude processes when evaluating a risky outcome, providing a better understanding of the possible mechanism underlying risky reward processing.

Keywords: probability weight, money magnitude, risky choice, neural dynamics, ERP

INTRODUCTION

Risky decision-making, which involves trade-offs between lotteries with differing magnitude and uncertainty, is ubiquitous in everyday life. Therefore, when making decisions among risky rewards, it is necessary to evaluate the subjective value of each risky reward. The subjective value of a risky reward depends on its probability and magnitude (Tversky and Kahneman, 1981; Brown and Braver, 2007). Prospect theory, an influential model of risky decision-making, suggests that the subjective value of a risky outcome depends on gains or losses relative to status quo and probability weighting function (Kahneman and Tversky, 1979; Camerer, 2000).

The neurocognitive mechanisms underlying risky decision-making involve several processes: valuation, choice, and feedback (Rangel et al., 2008; Liu et al., 2012). Previous neuroscience studies focused on the choice and feedback processes of risky decision-making, but the neural correlates for valuation of risky rewards are not well understood (see review by Chandrakumar et al., 2018). The focus of this study is on the temporal dynamics of the valuation process of risky rewards using an event-related brain potential (ERP) technique.

Neuroimaging studies have demonstrated that a number of brain regions including the ventromedial prefrontal cortex, amygdala, insula, anterior cingulate cortex (ACC), striatum, parietal, and temporal cortices are implicated in risk processing (Paulus and Frank, 2006; Berns et al., 2008; Hsu et al., 2009; Blankenstein et al., 2018). Several studies investigated the neural correlates of probability and magnitude of a risky reward. Berns and Bell (2012) measured independently the neural responses to magnitude and probability of a risky outcome by displaying serially magnitude and probability information. They found that the ventral and dorsal striatum were involved in the processes of magnitude and probability, respectively. These results demonstrate a second-order decision process, in which participants integrate judgments instead of information. In a study by Smith et al. (2009), high reward elicited more activation in several brain regions including the insula, amygdala, and posterior cingulate cortex when other parameters were held constant, as opposed to low reward. Low-probability reward induced more activation in the ACC than high-probability reward when other parameters were held constant.

Eye-tracking methodology has been used to investigate processes in risky decision-making (Rayner, 1998; Glöckner and Herbold, 2011). These studies suggested that risky decision-making relied mainly on automatic-intuitive processes, which were partially accounted for by automatic integration or simple heuristic models (Glöckner and Herbold, 2011; Fiedler and Glöckner, 2012; Venkatraman et al., 2014; Aimone and Ball, 2016). Eye-tracking studies have focused on risky choices in which two gambles were displayed simultaneously. Such paradigms did not allow us to distinguish valuation and choice processes. Furthermore, in real world, individuals usually face risky choice options serially.

Existing event-related brain potential (ERP) studies of risky decision-making focused on responses to risk-related decision and feedback. Only a minority of ERP studies have focused on the neural response to risky options (see review by Chandrakumar et al., 2018). Both feedback-related negativity (FRN) and P300 are two important ERP components involved in the risk process. The FRN, which is often known as reward positivity (RewP) associated with outcomes processing in the context of gains in contrast with losses (Foti et al., 2012; Proudfit, 2015; Yaple et al., 2018a,b), is larger following negative feedback relative to positive feedback (Wu and Zhou, 2009; Polezzi et al., 2010; Yang and Zhang, 2011; Yang et al., 2015; Zhao et al., 2016; Kardos et al., 2017). The P300, which is thought to reflect the outcome of stimulus evaluation and decision-making, was pronounced in response to the selection of a risky option and positive feedback (Yeung and Sanfey, 2004; Sato et al., 2005; Oberg et al., 2011; Schuermann et al., 2012; Wang et al., 2015).

While previous ERP studies have yielded important insights into the neural mechanisms of risky decision-making, there are limitations. First, risky decision-making involves valuation and choice processes, with evaluation of a risky reward most relevant to the valuation process (Rangel et al., 2008; Liu et al., 2012). Previous ERP paradigms, in which the participants' task was to decide whether or not to accept a risky bet, did not allow one to distinguish among valuation and choice processes. Furthermore, evaluation of a risky reward involves its probability weight and magnitude, but previous ERP studies did not focus on these two components.

In this study, we developed a risky choice task to investigate neural mechanisms underlying probability weight and magnitude of risky rewards based on study paradigms derived from the intertemporal choice literature (Pine et al., 2009; Xia et al., 2017), given that there are a number of similarities between delay and probability discounting (Green and Myerson, 2004; Madden and Bickel, 2010; McKerchar and Renda, 2012). In our paradigm, each choice consisted of two risky options, which were first presented serially, then presented simultaneously. This allowed us to separate risky rewards valuation and selection processes. By controlling for the effects of probability and magnitude respectively, we could explore the neural mechanisms underlying probability weight and magnitude during evaluation of a risky reward.

According to previous research, several ERP components are associated with magnitude and probability processes. Based on these, we analyzed the ERP response related to probability weight and money magnitude in the evaluation of a risky reward. Since frontal P200 may be involved in stimulus evaluation and quick assessment (Boudreau et al., 2009; Lau et al., 2013), a hypothesis, in which the frontal P200 would reflect the difference between high- and low-probability rewards, was proposed. A second evaluated component was medial frontal negativity (MFN)[1], which represents the early appraisal of feedback and is more pronounced for bad outcomes compared to good outcomes (Hajcak et al., 2006; Holroyd et al., 2006; Hewig et al., 2007; Boksem and de Cremer, 2010; Huang and Yu, 2014; Umemoto et al., 2017). In this study, when the magnitude of options was held constant, the high-probability rewards were considered "good" outcomes compared to low-probability rewards. Therefore, we predicted that the MFN would reflect the difference between high- and low-probability rewards. Similar predictions for the magnitude of risky rewards were made. Furthermore, the P300 has been shown to be sensitive to outcome evaluation, including the magnitude and valence of rewards (Goyer et al., 2008; Wu and Zhou, 2009; Harris et al., 2013; Righi et al., 2014). It is possible that the P300 would also encode the probability weight of risky rewards. Therefore, we hypothesized that the P300 or a later component would reflect the process of probability weight and money magnitude.

MATERIALS AND METHODS

Participants

A total of 20 right-handed undergraduates were recruited. Twelve females and eight males participated. They were 20–25 years

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[1] The MFN is a class of ERP components which include the FRN and ERN. The MFN has been proposed to reflect a motivational/affective evaluation of negative outcomes. Both feedback and stimulus information elicit MFN. The MFN in the context of feedback-locked ERPs could reflect whether outcomes matched expectations, while the MFN in the context of stimulus-locked ERPs could reflect whether the events violated (social and non-social) expectancy (Holroyd and Coles, 2002; Goyer et al., 2008; Boksem and de Cremer, 2010; Schuermann et al., 2012). This study focused on stimulus-locked ERPs.

of age with a mean age of 22.35 (*SD* = 1.59). All participants had normal or corrected-to-normal visual acuity and no history of neurological or mental disease. All subjects signed an informed consent prior to the experiment, which was performed in accordance with the Declaration of Helsinki and was approved by the Ethics Committee of Reinhard Selten Laboratory, Nankai University. The participants received an average of 65 Chinese yuan (approximately $10) (Krajbich et al., 2012; Li et al., 2016; Yaple et al., 2017, 2018a,b).

Task and Stimuli

According to Prospect Theory (Kahneman and Tversky, 1979), the subjective value (*V*) of a risky gamble is given by:

$$V = \sum_{i=1}^{n} \pi\left(p_i\right) u\left(x_i\right)$$

In the present study, we focused on the evaluation of risky rewards. Therefore, each risky option consisted of a risky reward and a zero reward. Therefore, the subjective value (*V*) of a risk option was expressed as:

$$V = \pi\left(p\right) \times u\left(x\right)$$

The function $\pi(p)$ represents the subjective probability to objective probability p, with $u(x)$ the undiscounted utility of a reward (x).

This study tried to explore neural processing of probability weight and money magnitude of a risky reward. Since the subjective value of a risky reward is determined by the magnitude and probability of its receipt, an experimental paradigm was designed to allow comparison based on: (1) different probabilities but same money magnitude, and (2) different money magnitude but same probability. To obtain subjective utility related to probability, two types of stimuli were considered: winning CNY50 at the probability of 0.2 (low probability, LP) and CNY50 at the probability of 0.5 (high probability, HP). Similarly, for money magnitude, we considered two types of stimuli: winning CNY15 at the probability of 0.66 (small magnitude, SM) and CNY40 at the probability of 0.66 (large magnitude, LM). In addition, in order to improve the reality of the experiment and decrease the risk that participants will be bored, some stimuli including CNY10 by 0.99, CNY30 by 0.33, CNY60 by 0.33, and CNY20 by 0.99 were defined as filling materials.

The task of the participants was to choose between two options with different magnitude and probability of occurrence. Each option of a choice was presented serially to separate decision-making and option valuation processes. At the end of the experiment, two of the participant's choices were selected at random and used for subject payment.

Procedure

The rules of the experimental task were instructed to the participants by explaining written instructions. The task was performed in a quiet and isolated laboratory. The participants were told that they would be paid for participation after completion of the experiment. The recording session took approximately 30 min.

After 8 practice trials, a total of 100 trials were randomly divided into 2 blocks with 50 trials each. Each trial was created through the following sequence. In each trial, a cross was first displayed in the center of a screen for 800–1,200 ms. Afterward, option 1 was presented for 1,500 ms. Then, after a cross of 800–1,200 ms, option 2 was presented for 1,500 ms. Next, the choice was displayed until a response had been made. The presentation of the two options for each type of stimuli was counterbalanced in a random order across trials. Then, their choice was shown for 1,000 ms, after which a blank screen was displayed for 1,000 ms, and then the next trial started (**Figure 1**).

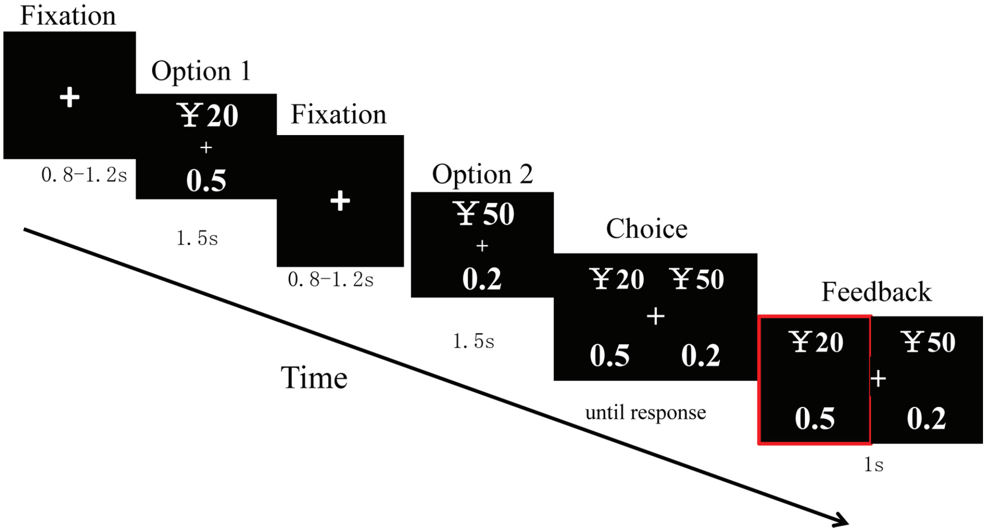

FIGURE 1 | Sequence of trail events.

Electroencephalography (EEG) Recording and Analysis

EEGs were continuously acquired at a 1,000 Hz sampling rate with a Neuroscan Synamp2 Amplifier, by using an electrode cap with Ag/AgCl electrodes mounted according to the extended international 10–20 system. The EEG signals were amplified online (band pass: 0.05–100 Hz). All rows of electrode recordings were referenced online to the left mastoid, and they were re-referenced offline to the average of the left and right mastoid. Electrode impedance was kept under 5 kΩ. Following the electrode application, the participants sat in a comfortable chair located in a shielded room and were asked to fix on the center of the computer display located 1 m away from their eyes during the experiment.

EEG epochs of 1,000 ms (from −200 to 800 ms after the onset of stimulus) were extracted offline, and the 200-ms pre-stimulus defined as baseline. Ocular artifacts were corrected. Trials contaminated by amplifier clipping, bursts of electromyographic activity or peak-to-peak deflection exceeding ±75 μV were excluded from further analysis. The remaining trials were baseline corrected. The EEG segments were averaged separately for probability type (HP vs. LP) and magnitude type (LM vs. SM). Averaged ERPs were digitally filtered with a low-pass filter at 30 Hz. Within-subject repeated measure analysis of variance (ANOVA) were used to analyze ERP data. Behavior and ERP data were statistically analyzed using SPSS (version 22, SPSS Inc., Chicago, IL, USA). A Greenhouse-Geisser correction for violation of sphericity assumption was applied when the degrees of freedom were more than one. The significance level was set at 0.05 for all analyses. To control for family-wise error for multiple *t*-tests, *p* were Bonferroni corrected.

Based on the visual inspection of the grand-average waveforms, three components were analyzed. The frontal P200 was measured as peak amplitude between 150 and 250 ms after stimulus onset at F3, Fz, F4, FC3, FCz, and FC4 (Polezzi et al., 2008; Molinaro and Carreiras, 2010; Gui et al., 2016). The MFN component was measured as peak amplitude between 250 and 350 ms after stimulus onset at F3, Fz, F4, FC3, FCz, and FC4 (Boksem and de Cremer, 2010; Schuermann et al., 2012; Huang and Yu, 2014; Xia et al., 2017). The LPP was measured as mean amplitude between 450 and 650 ms after stimulus onset at CP3, CPz, CP4, P3, Pz, and P4 (Harris et al., 2013; Righi et al., 2014; Gui et al., 2016). ERP analyses were conducted by repeated-measure ANOVAs, with electrode (for P200 and MFN: F3, Fz, F4, FC3, FCz, and FC4, for LPP: CP3, CPz, CP4, P3, Pz, and P4) and probability (high, low), and electrode and magnitude (large, small), respectively.

RESULTS

Behavioral Results

Behavioral results are shown in **Table 1**. For the choice of CNY50 by 0.2 probabilities and CNY15 by 0.66 probabilities, 44.60% of decisions chose the former. For the choice of CNY50 by 0.5 probabilities and CNY40 by 0.66 probabilities, 38.73% of decisions chose the former. The average response time was 775.98 ms (*SD* = 611.5195) and 719.52 ms (*SD* = 413.1792), respectively. For the choice of CNY50 by 0.2 probabilities and CNY40 by 0.66 probabilities, all decisions chose the latter. For the choice of CNY50 by 0.5 probabilities and CNY15 by 0.66 probabilities, 95.24% of decisions chose the former. The average response time was 550.69 ms (*SD* = 204.8855) and 590.89 ms (*SD* = 268.96), respectively.

TABLE 1 | Behavioral results.

Choice type (option 1: option 2)	Percentage of option 1	Response time	Standard deviation
CNY 50 by 0.2: CNY 15 by 0.66	44.60%	775.98	611.5195
CNY 50 by 0.2: CNY 40 by 0.66	0.00%	550.69	204.8855
CNY 50 by 0.5: CNY 15 by 0.66	95.24%	590.89	268.9600
CNY 50 by 0.5: CNY 40 by 0.66	38.73%	719.52	413.1762

Participants took more response time to make decision between the choices in which the expected value of two options was similar, compared to choices in which there was large difference between the expected values of two options ($p = 0.02$). Based on formal logic, when the expected value of each option of a risky choice is similar, the higher level of conflict requires more brain resources for conflict resolution, which results in more response time.

Behavioral data showed that participants chose the option with largest expected value. This is consistent with previous studies and demonstrates that participants clearly understood the experimental task.

ERP Results for Probability Weight

P200

Figure 2 shows ERP waveforms and topographic maps for probability processes at Fz and FCz electrodes. In the frontal area, there was a significant main effect of P200 for probability levels [$F(1, 19) = 8.309$, $p = 0.010$, $\eta^2 = 0.304$], no main effect for laterality [$F(2, 38) = 3.899$, $p = 0.051$, $\eta^2 = 0.170$], and no interaction between probability levels and laterality [$F(2, 38) = 2.160$, $p = 0.145$, $\eta^2 = 0.102$] were found. In the frontal-central scalp area, significant main effects were found for probability levels [$F(1, 19) = 7.586$, $p = 0.013$, $\eta^2 = 0.285$] and laterality [$F(2, 38) = 5.117$, $p = 0.017$, $\eta^2 = 0.212$]. There was no interaction between probability levels and laterality [$F(2, 38) = 2.288$, $p = 0.126$, $\eta^2 = 0.107$]. High-probability rewards elicited more positive P200 than low-probability ones when the magnitude was kept constant.

MFN

As shown in **Figure 2,** in the frontal area, significant main effects of MFN were observed for probability levels [$F(1, 19) = 10.389$, $p = 0.004$, $\eta^2 = 0.353$] and laterality [$F(2, 38) = 5.490$, $p = 0.024$, $\eta^2 = 0.224$], but no interaction was found between probability levels and laterality [$F(2, 38) = 1.656$, $p = 0.211$, $\eta^2 = 0.080$]. In the frontal-central area, significant main effects of MFN were observed for probability levels [$F(1, 19) = 12.067$, $p = 0.003$, $\eta^2 = 0.388$] and laterality [$F(2, 38) = 5.443$, $p = 0.020$, $\eta^2 = 0.223$].

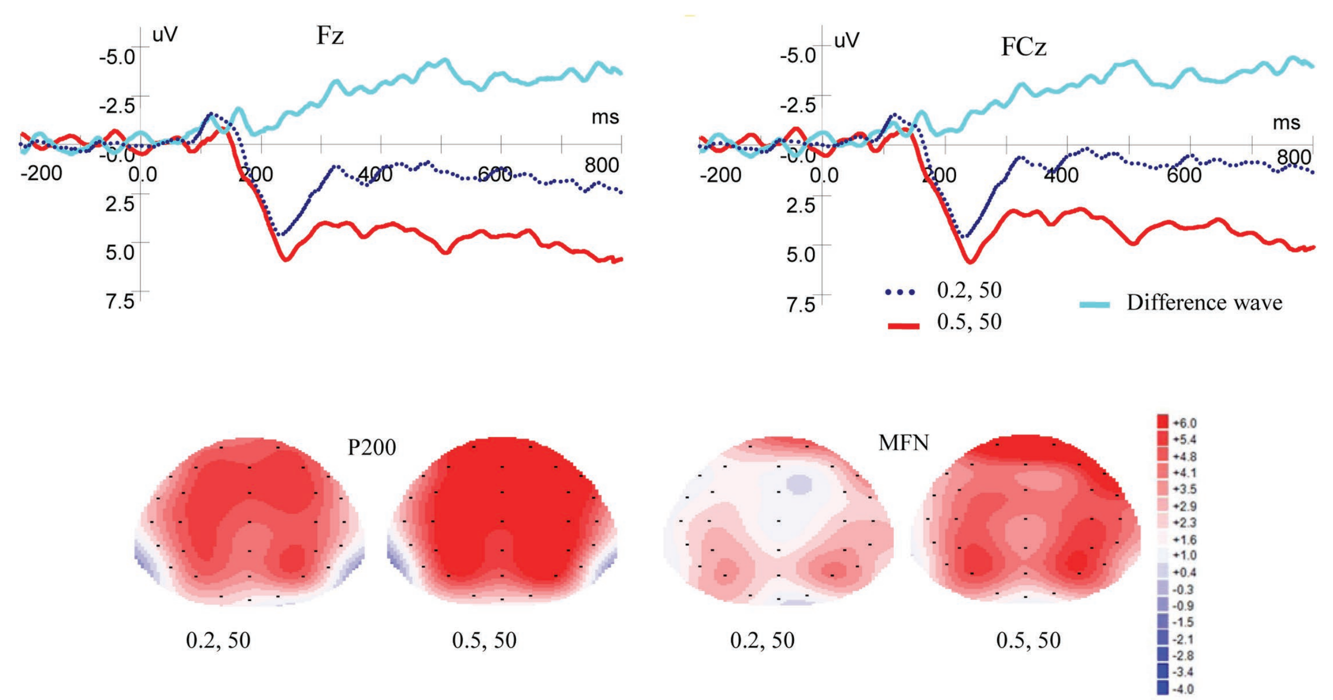

FIGURE 2 | Grand-averaged ERP waves at electrodes Fz and FCz for probability and topographic maps for P200 and MFN.

There was no interaction between probability levels and laterality [$F(2, 38) = 3.594$, $p = 0.053$, $\eta^2 = 0.159$]. These results showed that low-probability rewards elicited more negative MFN than high-probability ones, when the magnitude was kept constant.

LPP

Figure 3 shows ERP waveforms and topographic maps for probability processes at Pz and CPz electrodes. In the parietal area, a significant main effect for LPP was found for probability levels [$F(1, 19) = 17.599$, $p = 0.000$, $\eta^2 = 0.481$]. There were no significant main effect for laterality [$F(2, 38) = 2.418$, $p = 0.105$, $\eta^2 = 0.113$] and no interaction between probability levels and laterality [$F(2, 38) = 0.032$, $p = 0.935$, $\eta^2 = 0.002$]. In the central-parietal area, significant main effects for LPP was found for probability levels [$F(1, 19) = 19.374$, $p = 0.000$, $\eta^2 = 0.505$] and laterality [$F(2, 38) = 3.884$, $p = 0.043$, $\eta^2 = 0.170$], but no interaction was found between probability levels and laterality [$F(2, 38) = 0.033$, $p = 0.934$, $\eta^2 = 0.002$]. These results demonstrated that high-probability rewards elicited more positive LPP than low-probability ones, when the magnitude was kept constant.

ERP Results for Money Magnitude

P200

Figure 4 shows ERP waveforms and topographic maps for money magnitude at Fz and FCz electrodes. In the frontal area, there were no significant P200 effect for reward magnitude [$F(1, 19) = 0.093$, $p = 0.764$, $\eta^2 = 0.005$] and no interaction between magnitude and laterality [$F(2, 38) = 0.045$, $p = 0.921$, $\eta^2 = 0.002$]. But there was significant P200 effect for laterality [$F(2, 38) = 7.140$, $p = 0.002$, $\eta^2 = 0.273$]. In the frontal-central area, no significant P200 effects were observed for magnitude levels [$F(1, 19) = 0.095$, $p = 0.761$, $\eta^2 = 0.005$] and laterality [$F(2, 38) = 1.716$, $p = 0.198$, $\eta^2 = 0.083$]. There was no interaction between magnitude levels and laterality [$F(2, 38) = 0.059$, $p = 0.878$, $\eta^2 = 0.003$].

MFN

As shown in **Figure 4,** in the frontal area, significant main effects for MFN were found for magnitude levels [$F(1, 19) = 6.380$, $p = 0.021$, $\eta^2 = 0.251$] and laterality [$F(2, 38) = 13.866$, $p = 0.000$, $\eta^2 = 0.422$], but no interaction was found between magnitude levels and laterality [$F(2, 38) = 1.461$, $p = 0.246$, $\eta^2 = 0.071$]. In the frontal-central area, significant main effects for MFN were found for magnitude levels [$F(1, 19) = 5.619$, $p = 0.029$, $\eta^2 = 0.228$] and laterality [$F(2, 38) = 9.404$, $p = 0.001$, $\eta^2 = 0.331$], but no interaction was found between magnitude levels and laterality [$F(2, 38) = 0.735$, $p = 0.454$, $\eta^2 = 0.037$]. Given same probability weight, small rewards elicited more positive MFN than large ones.

LPP

Figure 5 shows ERP waveforms and topographic maps for magnitude at Pz and CPz electrodes. In the parietal area, no significant main effect of LPP was found for magnitude levels [$F(1, 19) = 1.937$, $p = 0.180$, $\eta^2 = 0.093$] and no interaction was found between magnitude levels and laterality [$F(2, 38) = 1.867$, $p = 0.176$, $\eta^2 = 0.089$]. There was no significant main effect for

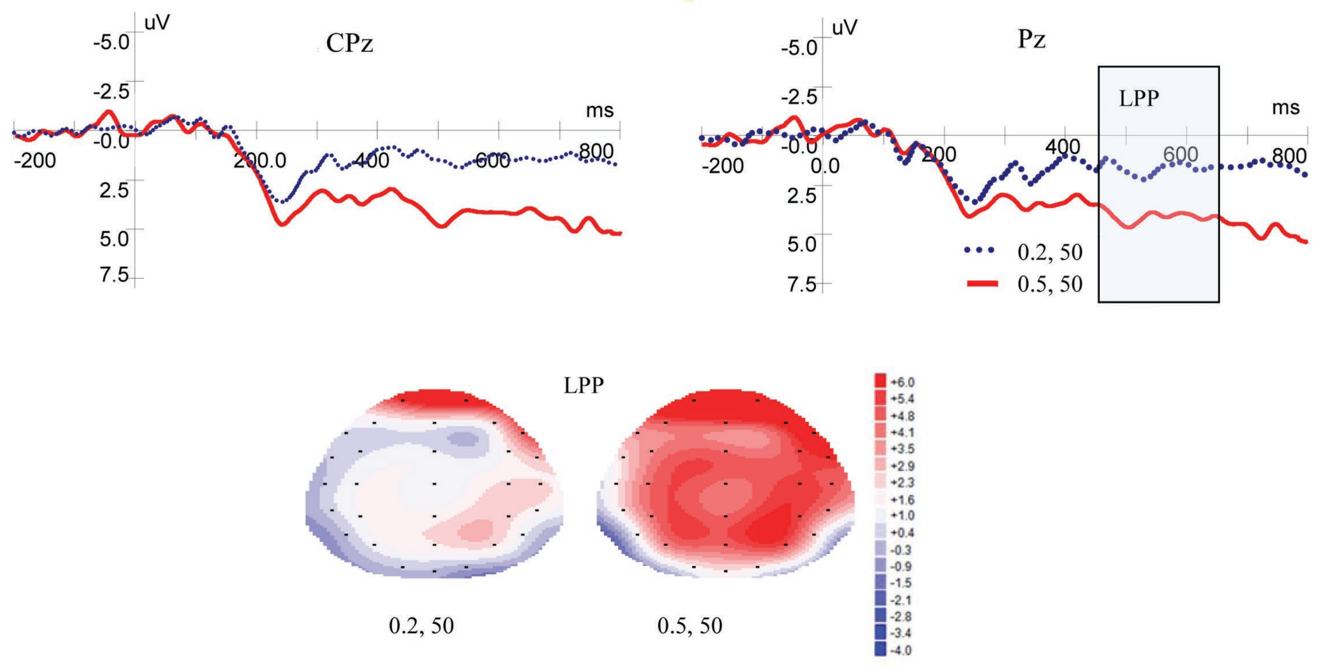

FIGURE 3 | Grand-averaged EPR waveforms at electrodes Pz and CPz for probability, and topographic maps for LPP.

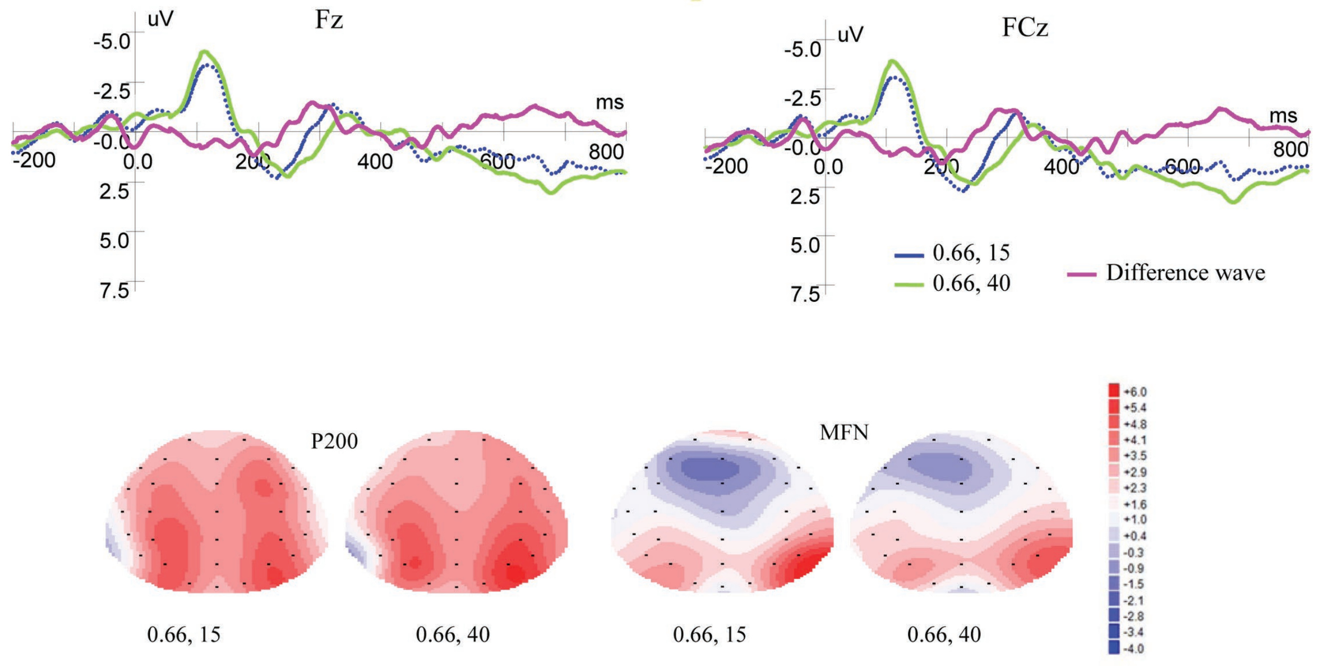

FIGURE 4 | Grand-averaged EPR waveforms at electrodes Fz and FCz for magnitude, and topographic maps for P200 and MFN.

laterality [$F(2, 38) = 1.651$, $p = 0.208$, $\eta^2 = 0.080$]. In the central-parietal area, no significant main effects of LPP were found for magnitude levels [$F(1, 19) = 1.431$, $p = 0.246$, $\eta^2 = 0.070$] or laterality [$F(2, 38) = 1.804$, $p = 0.186$, $\eta^2 = 0.087$], and no interaction was found between magnitude levels and laterality [$F(2, 38) = 0.676$, $p = 0.473$, $\eta^2 = 0.034$].

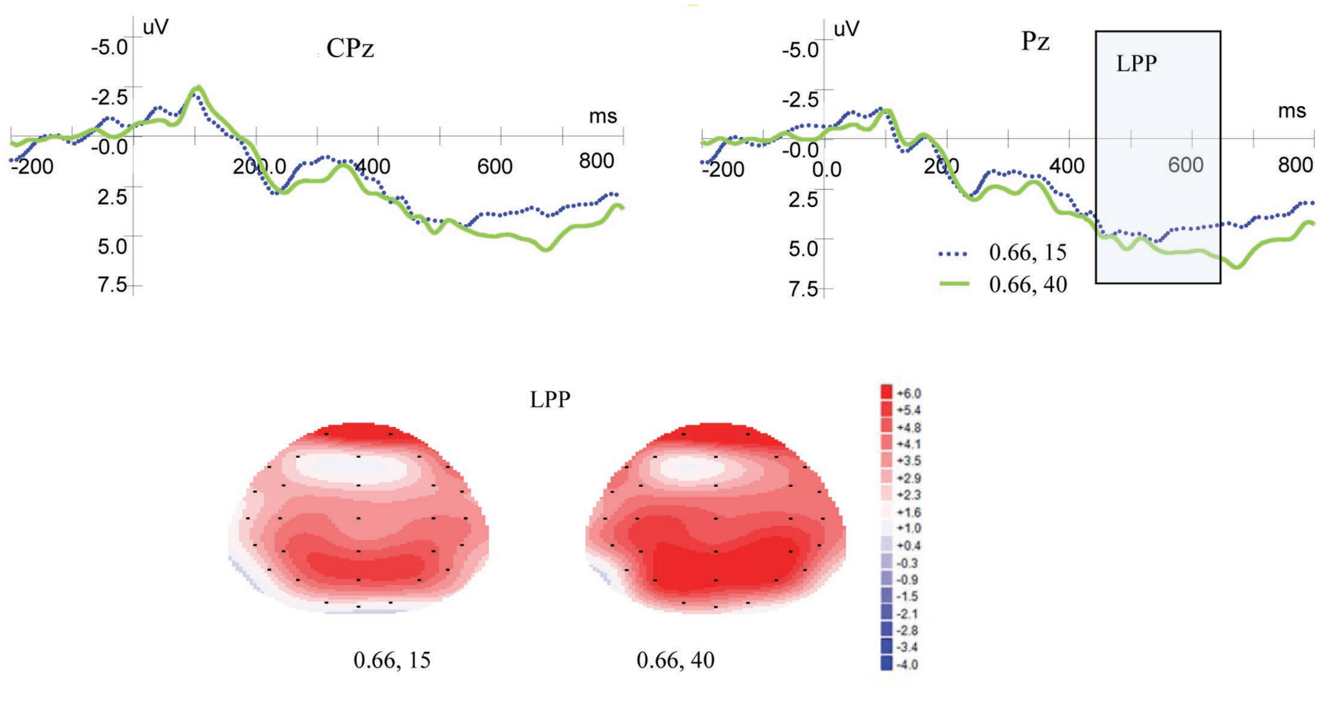

FIGURE 5 | Grand-averaged EPR waves at electrodes Pz and CPz for magnitude, and topographic maps for LPP.

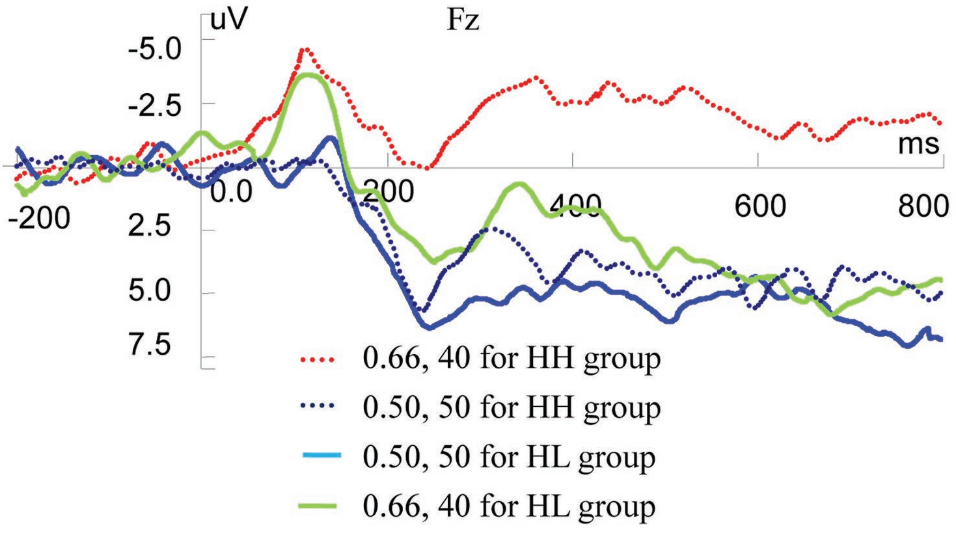

FIGURE 6 | Grand-averaged EPR waves at electrode Fz for different groups (HH, HL).

Relationships Among Evaluation and Risky Decision-Making Behaviors

In the present study, there were two types of normal choices: CNY50 by 0.2 probabilities (expected value (*EV*) = 10) and CNY15 by 0.66 probabilities (*EV* = 9.9), CNY50 by 0.5 probabilities (*EV* = 25) and CNY40 by 0.66 probabilities (*EV* = 26.4). Based on behavioral results, participants were divided into groups. For the choice of CNY50 by 0.2 and CNY15 by 0.66, 9 participants (LH) almost chose the former and 11 participants (LL) almost chose the latter. For the choice of CNY50 by 0.5 probabilities and CNY40 by 0.66 probabilities, 8 participants (HH) almost chose the former and 12 participants (HL) almost chose the latter.

We conducted independent *t*-test using ERP data on Fz to analyze the correlation among valuation of risky rewards and risky decision-making behaviors (**Figure 6**). Statistical results showed that there was no significant ERP difference between LH and LL groups when they observed CNY50 by 0.2 and CNY15 by 0.66, respectively. However, when observing CNY50 by 0.5 and CNY40 by 0.66 respectively, HH and HL groups displayed different ERP valuation. For CNY50 by 0.5, there was no significant ERP difference between HH and HL groups, but for CNY40 by 0.66, two types of participants expressed different valuation. For P200 component, the mean amplitudes were 1.1040 and 4.9620 μV in HH and HL groups, respectively ($t = -2.025$, $df = 18$, $p = 0.058$). For MFN component, the mean amplitudes were −4.0098 and 0.2311 μV in HH and HL groups, respectively ($t = -1.675$, $df = 18$, $p = 0.111$). For the LPP component, the mean amplitudes were −1.8682 and 4.5597 μV in HH and HL groups, respectively ($t = -2.437$, $df = 18$, $p = 0.025$).

DISCUSSION

Risky decision-making involves risky reward valuation, choice, and feedback processes. This study focused on risky reward valuation. This investigation assessed the neural dynamics involved in the processing of probability weight and money magnitude. ERP results demonstrated distinct temporal dynamics for probability weight and money magnitude processes. The early frontal P200, MFN, and LPP components all represented the process of probability weight; however, only the MFN component was associated with the process of money magnitude when evaluating a risky reward.

Frontal P200 revealed a significant main effect of probability weight on the frontal and frontal-central areas, but no significant main effect of money magnitude for a risky reward. Low-probability reward elicited less positive P200 amplitude when compared to high-probability reward at the same magnitude. Previous studies showed that P200, the probable sources of which may be the mesotelencephalic dopamine reward system, likely associates with stimulus evaluation and quick assessment (Boudreau et al., 2009; Chen et al., 2009). The P200 component has been shown to be involved in attention to relevant cues including reward-related stimuli (Molinaro and Carreiras, 2010; Lau et al., 2013; Gui et al., 2016). Several ERP studies, which explored the processing of reward, found that a reward condition elicited larger P200 compared to a non-reward condition (Martin and Potts, 2004; Franken et al., 2010). The relationships between low- and high-probability rewards were similar to those relationships. Schuermann et al. (2012) found that P200 was enhanced on negative feedbacks in high-risk compared to low-risk choices, which suggests that large negative prediction errors are already processed in the P200 time range. Hence, our findings are consistent and suggest that participants detected the initial feature of probability, not magnitude at the early stage of risky option processing.

The MFN component, which reflects the impact of dopamine-dependent reward signals on the ACC, may represent the evaluation of reward value (Gehring, 2002; Holroyd and Coles, 2002; Proudfit, 2015). In the present study, consistent with this classical theory, the MFN component showed significant main effects of both probability weight and money magnitude of a risky reward. Given the same magnitude, low-probability options evoked a more negative MFN as compared to high-probability options. Moreover, small magnitude induced a more pronounced MFN than large magnitude for the same probability weight. Existing studies demonstrated that the MFN component reflects the early appraisal of feedback, in which the MFN response to unfavorable outcomes is larger compared to favorable outcomes (Holroyd et al., 2006; Goyer et al., 2008; Boksem and de Cremer, 2010; Broyd et al., 2012; Huang and Yu, 2014; Umemoto et al., 2017). Our results are consistent with those findings. Since risky decision-making is ubiquitous, high-probability rewards are considered better than low-probability ones for the same magnitude. In other words, a high-probability reward is a "good" outcome, relative to a low-probability reward when the magnitude is constant. Likewise, large rewards are considered better than small rewards with the same probability weight.

The LPP component has been mainly associated with affective and emotional processing (Ferrari et al., 2011; Righi et al., 2012). Many studies have found positive and negative stimuli to elicit larger LPP amplitude than neural stimuli, which suggests that more brain resources are allocated to affective stimuli (Foti and Hajcak, 2008; Hua et al., 2014; Zhang et al., 2014; Guo et al., 2018). In this study, LPP was more positive for high-probability than low-probability reward, demonstrating that participants paid more attention to high-probability reward. The study of Harris et al. (2013) found that LPP reflected process differences between liked and disliked food items. Those results suggest LPP is related to valuation modulation. The relationship between liked and disliked foods is similar to that between high- and low-probability rewards. Wu et al. (2011) investigated the neural response to selection of risky rewards. They found that medial prefrontal cortex (mPFC) involved in the process of magnitude, and mPFC and ACC correlated with probability. Given that P300 and LPP amplitude variation is related to the striatum (Pfabigan et al., 2014) and the MFN is correlated with ACC and mPFC (Gehring, 2002; Boksem and de Cremer, 2010), their findings support our conclusions.

In summary, this study investigated neural dynamics of the processes associated with probability weight and money magnitude in the evaluation of a risky reward. ERP results demonstrated P200, MFN, and LPP components to reflect the processing of probability weight, while only the MFN component reflected the processing of money magnitude when evaluating a risky reward. These findings contribute to an understanding of the temporal course of processing probability weight and money magnitude during risky choices.

AUTHOR CONTRIBUTIONS

GW and JL conceived and designed this study. GW, JL, PW, and CZ designed experimental stimuli and procedures. CZ and JP implemented experimental protocols and collected data. SL and GW analyzed data. GW and JL wrote the paper.

FUNDING

This work was supported by the National Natural Science Fund of China (Grant numbers: 71673152 and 71533002), the National Social Science Foundation of China (Grant number: 16BJY035), and Shandong Provincial Natural Science Fund, China (Grant number: ZR2016GM07).

REFERENCES

Aimone, J. A., and Ball, S. (2016). It's not what you see but how you see it: using eye-tracking to study the risky decision-making process. *J. Neurosci. Psychol. Econ.* 9, 137–144. doi: 10.1037/npe0000061

Berns, G. S., and Bell, E. (2012). Striatal topography of probability and magnitude information for decisions under uncertainty. *NeuroImage* 59, 3166–3172. doi: 10.1016/j.neuroimage.2011.11.008

Berns, G. S., Capra, C. M., Chappelow, J., Moore, S., and Noussair, C. (2008). Nonlinear neurobiological probability weighting functions for aversive outcomes. *NeuroImage* 39, 2047–2057. doi: 10.1016/j.neuroimage.2007.10.028

Blankenstein, N. E., Schreuders, E., Peper, J. S., Crone, E. A., and Van Duijvenvoorde, A. C. K. (2018). Individual differences in risk-taking tendencies modulate the neural processing of risky and ambiguous decision-making in adolescence. *NeuroImage* 172, 663–673. doi: 10.1016/j.neuroimage.2018.01.085

Boksem, M. A. S., and de Cremer, D. (2010). Fairness concerns predict medial frontal negativity amplitude in ultimatum bargaining. *Soc. Neurosci.* 5, 118–128. doi: 10.1080/17470910903202666

Boudreau, C., McCubbins, M. D., and Coulson, S. (2009). Knowing when to trust others: an ERP study of decision making after receiving information from unknown people. *Soc. Cogn. Affect. Neurosci.* 4, 23–34. doi: 10.1093/scan/nsn034

Brown, J. W., and Braver, T. S. (2007). Risk prediction and aversion by anterior cingulate cortex. *Cogn. Affect. Behav. Neurosci.* 7, 266–277. doi: 10.3758/CABN.7.4.266

Broyd, S. J., Richards, H. J., Helps, S. K., Chronaki, G., Bamford, S., and Sonuga-Barke, E. J. S. (2012). An electrophysiological monetary incentive delay (e-mid) task: a way to decompose the different components of neural response to positive and negative monetary reinforcement. *J. Neurosci. Methods* 209, 40–49. doi: 10.1016/j.jneumeth.2012.05.015

Camerer, C. (2000). "Prospect theory in the wild: evidence from the field" in *Choices, values and frames*. eds. D. Kahneman and A. Tversky (New York: Cambridge University Press), 288–300.

Chandrakumar, D., Feuerriegel, D., Bode, S., Grech, M., and Keage, H. A. D. (2018). Event-related potentials in relation to risk-taking: a systematic review. *Front. Behav. Neurosci.* 12:111. doi: 10.3389/fnbeh.2018.00111

Chen, P., Qiu, J., Li, H., and Zhang, Q. (2009). Spatiotemporal cortical activation underlying dilemma decision-making: an event-related potential study. *Biol. Psychol.* 82, 111–115. doi: 10.1016/j.biopsycho.2009.06.007

Ferrari, V., Bradley, M. M., Codispoti, M., and Lang, P. J. (2011). Repetitive exposure: brain and reflex measures of emotion and attention. *Psychophysiology* 48, 515–522. doi: 10.1111/j.1469-8986.2010.01083.x

Fiedler, S., and Glöckner, A. (2012). The dynamics of decision making in risky choice: an eye-tracking analysis. *Front. Psychol.* 3:335. doi: 10.3389/fpsyg.2012.00335

Foti, D., and Hajcak, G. (2008). Deconstructing reappraisal: descriptions preceding arousing pictures modulate the subsequent neural response. *J. Cogn. Neurosci.* 20, 977–988. doi: 10.1162/jocn.2008.20066

Foti, D., Kotov, R., Bromet, E., and Hajcak, G. (2012). Beyond the broken error-related negativity: functional and diagnostic correlates of error processing in psychosis. *Biol. Psychiatry* 71, 864–872. doi: 10.1016/j.biopsych.2012.01.007

Franken, I. H., Van den Berg, I., and Van Strien, J. W. (2010). Individual differences in alcohol drinking frequency are associated with electrophysiological responses to unexpected nonrewards. *Alcohol. Clin. Exp. Res.* 34, 702–707. doi: 10.1111/j.1530-0277.2009.01139.x

Gehring, W. J. (2002). The medial frontal cortex and the rapid processing of monetary gains and losses. *Science* 295, 2279–2282. doi: 10.1126/science.1066893

Glöckner, A., and Herbold, A. K. (2011). An eye-tracking study on information processing in risky decisions: evidence for compensatory strategies based on automatic processes. *J. Behav. Decis. Mak.* 24, 71–98. doi: 10.1002/bdm.684

Goyer, J. P., Woldorff, M. G., and Huettel, S. A. (2008). Rapid electrophysiological brain responses are influenced by both valence and magnitude of monetary rewards. *J. Cogn. Neurosci.* 20, 2058–2069. doi: 10.1162/jocn.2008.20134

Green, L., and Myerson, J. (2004). A discounting framework for choice with delayed and probabilistic rewards. *Psychol. Bull.* 130, 769–792. doi: 10.1037/0033-2909.130.5.769

Gui, D.-Y., Li, J.-Z., Li, X., and Luo, Y. (2016). Temporal dynamics of the interaction between reward and time delay during intertemporal choice. *Front. Psychol.* 7:1526. doi:10.3389/fpsyg.2016.01526

Guo, F., Wang, X. S., Liu, W. L., and Ding, Y. (2018). Affective preference measurement of product appearance based on event-related potentials. *Cogn. Tech. Work* 20, 299–308. doi: 10.1007/s10111-018-0463-5

Hajcak, G., Moser, J. S., Holroyd, C. B., and Simons, R. F. (2006). The feedback-related negativity reflects the binary evaluation of good versus bad outcomes. *Biol. Psychol.* 71, 148–154. doi: 10.1016/j.biopsycho.2005.04.001

Harris, A., Hare, T., and Rangel, A. (2013). temporally dissociable mechanisms of self-control: early attentional filtering versus late value modulation. *J. Neurosci.* 33, 18917–18931. doi: 10.1523/JNEUROSCI.5816-12.2013

Hewig, J., Trippe, R., Hecht, H., Coles, M. G., Holroyd, C. B., and Miltner, W. H. (2007). Decision-making in blackjack: an electrophysiological analysis. *Cereb. Cortex* 17, 865–877. doi: 10.1093/cercor/bhk040

Holroyd, C. B., and Coles, M. G. H. (2002). The neural basis of human error processing: reinforcement learning, dopamine, and the error-related negativity. *Psychol. Rev.* 109, 679–709. doi: 10.1037/0033-295X.109.4.679

Holroyd, C. B., Hajcak, G., and Larsen, J. T. (2006). The good, the bad and the neutral: electrophysiological responses to feedback stimuli. *Brain Res.* 1105, 93–101. doi: 10.1016/j.brainres.2005.12.015

Hsu, M., Krajbich, I., Zhao, C., and Camerer, C. F. (2009). Neural response to reward anticipation under risk is nonlinear in probabilities. *J. Neurosci.* 29, 2231–2237. doi: 10.1523/JNEUROSCI.5296-08.2009

Hua, M., Han, Z. R., Chen, S., Yang, M., Zhou, R., and Hu, F. (2014). Late positive potential (LPP) modulation during affective picture processing in preschoolers. *Biol. Psychol.* 101, 77–81. doi: 10.1016/j.biopsycho.2014.06.006

Huang, Y., and Yu, R. (2014). The feedback-related negativity reflects "more or less" prediction error in appetitive and aversive conditions. *Front. Neurosci.* 8:108. doi: 10.3389/fnins.2014.00108

Kahneman, D., and Tversky, A. (1979). Prospect theory: an analysis of decision under risk. *Econometrica* 47, 263–291. doi: 10.2307/1914185

Kardos, Z., Tóth, B., Boha, R., File, B., and Molnár, M. (2017). Age-dependent characteristics of feedback evaluation related to monetary gains and losses. *Int. J. Psychophysiol.* 122, 42–49. doi: 10.1016/j.ijpsycho.2016.05.007

Krajbich, I., Lu, D., Camerer, C., and Rangel, A. (2012). The attentional drift-diffusion model extends to simple purchasing decisions. *Front. Psychol.* 3:193. doi: 10.3389/fpsyg.2012.00193

Lau, E. F., Holcomb, P. J., and Kuperberg, G. R. (2013). Dissociating N400 effects of prediction from association in single-word contexts. *J. Cogn. Neurosci.* 25, 484–502. doi: 10.1162/jocn_a_00328

Li, S., Du, X.-L., Li, Q., Xuan, Y.-H., Wang, Y., and Rao, L.-L. (2016). ERP correlates of verbal and numerical probabilities in risky choices: a two-stage probability processing view. *Front. Hum. Neurosci.* 9:717. doi: 10.3389/fnhum.2015.00717

Liu, L., Feng, T., Wang, J., and Li, H. (2012). The neural dissociation of subjective valuation from choice processes in intertemporal choice. *Behav. Brain Res.* 231, 40–47. doi: 10.1016/j.bbr.2012.02.045

Madden, G. J., and Bickel, W. K. (eds.) (2010). *Impulsivity: The behavioral and neurological science of discounting*. Washington, D.C.: American Psychological Association.

Martin, L. E., and Potts, G. F. (2004). Reward sensitivity in impulsivity. *NeuroReport* 15, 1519–1522. doi: 10.1097/01.wnr.0000132920.12990.b9

Mckerchar, T. L., and Renda, C. R. (2012). Delay and probability discounting in humans: an overview. *Psychol. Rec.* 62, 817–834. doi: 10.1007/BF03395837

Molinaro, N., and Carreiras, M. (2010). Electrophysiological evidence of interaction between contextual expectation and semantic integration during the processing of collocations. *Biol. Psychol.* 83, 176–190. doi: 10.1016/j.biopsycho.2009.12.006

Oberg, S. A. K., Christie, G. J., and Tata, M. S. (2011). Problem gamblers exhibit reward hypersensitivity in medial frontal cortex during gambling. *Neuropsychologia* 49, 3768–3775. doi: 10.1016/j.neuropsychologia.2011.09.037

Paulus, M. P., and Frank, L. R. (2006). Anterior cingulate activity modulates nonlinear decision weight function of uncertain prospects. *NeuroImage* 30, 668–677. doi: 10.1016/j.neuroimage.2005.09.061

Pfabigan, D. M., Seidel, E.-M., Sladky, R., Hahn, A., Paul, K., Grahl, A., et al. (2014). P300 amplitude variation is related to ventral striatum BOLD response during gain and loss anticipation: an EEG and fMRI experiment. *NeuroImage* 96, 12–21. doi: 10.1016/j.neuroimage.2014.03.077

Pine, A., Seymour, B., Roiser, J. P., et al. (2009). Encoding of marginal utility across time in the human brain. *J. Neurosci.* 29, 9575–9581. doi: 10.1523/JNEUROSCI.1126-09.2009

Polezzi, D., Sartori, G., Rumiati, R., Vidotto, G., and Daum, I. (2010). Brain correlates of risky decision-making. *NeuroImage* 49, 1886–1894. doi: 10.1016/j.neuroimage.2009.08.068

Polezzi, D., Lotto, L., Daumc, I., Sartori, G., and Rumiati, R. (2008). Predicting outcomes of decisions in the brain. *Behav. Brain Res.* 187, 116–122. doi: 10.1016/j.bbr.2007.09.001

Proudfit, G. H. (2015). The reward positivity: from basic research on reward to a biomarker for depression. *Psychophysiology* 52, 449–459. doi: 10.1111/psyp.12370

Rangel, A., Camerer, C., and Montague, P. R. (2008). A framework for studying the neurobiology of value-based decision making. *Nat. Rev. Neurosci.* 9, 545–556. doi: 10.1038/nrn2357

Rayner, K. (1998). Eye movements in reading and information processing: 20 years of research. *Psychol. Bull.* 124, 372–422. doi: 10.1037/0033-2909.124.3.372

Righi, S., Marzi, T., Toscani, M., Baldassi, S., Ottonello, S., and Viggiano, M. P. (2012). Fearful expressions enhance recognition memory: electrophysiological evidence. *Acta Psychol.* 139, 7–18. doi: 10.1016/j.actpsy.2011.09.015

Righi, S., Orlando, V., and Marzi, T. (2014). Attractiveness and affordance shape tools neural coding: insight from ERPs. *Int. J. Psychophysiol.* 91, 240–253. doi: 10.1016/j.ijpsycho.2014.01.003

Sato, A., Yasuda, A., Ohira, H., Miyawaki, K., Nishikawa, M., Kumano, H., et al. (2005). Effects of value and reward magnitude on feedback negativity and p300. *NeuroReport* 16, 407–411. doi: 10.1097/00001756-200503150-00020

Schuermann, B., Endrass, T., and Kathmann, N. (2012). Neural correlates of feedback processing in decision-making under risk. *Front. Hum. Neurosci.* 6:204. doi: 10.3389/fnhum.2012.00204

Smith, B. W., Mitchell, D. G. V., Hardin, M. G., Jazbec, S., Fridberg, D., Blair, R. J. R., et al. (2009). Neural substrates of reward magnitude, probability, and risk during a wheel of fortune decision-making task. *NeuroImage* 44, 600–609. doi: 10.1016/j.neuroimage.2008.08.016

Tversky, A., and Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science* 211, 453–458. doi: 10.1126/science.7455683

Umemoto, A., Hajihosseini, A., Yates, M. E., and Holroyd, C. B. (2017). Reward-based contextual learning supported by anterior cingulate cortex. *Cogn. Affect. Behav. Neurosci.* 17, 642–651. doi: 10.3758/s13415-017-0502-3

Venkatraman, V., Payne, J. W., and Huettel, S. A. (2014). An overall probability of winning heuristic for complex risky decisions: choice and eye fixation evidence. *Organ. Behav. Hum. Decis. Process.* 125, 73–87. doi: 10.1016/j.obhdp.2014.06.003

Wang, L., Zheng, J., Huang, S., and Sun, H. (2015). P300 and decision making under risk and ambiguity. *Comput. Intell. Neurosci.* 2015, 1–7. doi: 10.1155/2015/108417

Wu, S.-W., Delgado, M. R., and Maloney, L. T. (2011). The neural correlates of subjective utility of monetary outcome and probability weight in economic and in motor decision under risk. *J. Neurosci.* 31, 8822–8831. doi: 10.1523/JNEUROSCI.0540-11.2011

Wu, Y., and Zhou, X. (2009). The p300 and reward valence, magnitude, and expectancy in outcome evaluation. *Brain Res.* 1286, 114–122. doi: 10.1016/j.brainres.2009.06.032

Xia, L., Gu, R., Zhang, D., and Luo, Y. (2017). Anxious individuals are impulsive decision-makers in the delay discounting task: an erp study. *Front. Behav. Neurosci.* 11, 1–11. doi: 10.3389/fnbeh.2017.00005

Yang, J., and Zhang, Q. (2011). Electrophysiological correlates of decision-making in high-risk versus low-risk conditions of a gambling game. *Psychophysiology* 48, 1456–1461. doi: 10.1111/j.1469-8986.2011.01202.x

Yang, Q., Tang, P., Gu, R., Luo, W., and Luo, Y. (2015). Implicit emotion regulation affects outcome evaluation. *Soc. Cogn. Affect. Neurosci.* 10, 824–831. doi: 10.1093/scan/nsu124

Yaple, Z., Martinezsaito, M., Feurra, M., Shestakova, A., and Klucharev, V. (2017). Transcranial alternating current stimulation modulates risky decision making in a frequency-controlled experiment. *eNeuro* 4, e0136–17. doi: 10.1523/ENEURO.0136-17.2017

Yaple, Z., Martinez-Saito, M., Novikov, N., Altukhov, D., Shestakova, A., and Klucharev, V. (2018a). Power of feedback-induced beta oscillations reflect omission of rewards: evidence from an EEG gambling study. *Front. Neurosci.* 12:776. doi: 10.3389/fnins.2018.00776

Yaple, Z., Shestakova, A., and Klucharev, V. (2018b). Feedback-related negativity reflects omission of monetary gains: evidence from ERP gambling study. *Neurosci. Lett.* 686, 145–149. doi: 10.1016/j.neulet.2018.09.007

Yeung, N., and Sanfey, A. (2004). Independent coding of reward magnitude and valence in the human brain. *J. Neurosci.* 24, 6258–6264. doi: 10.1523/JNEUROSCI.4537-03.2004

Zhang, D., Gu, R., Broster, L. S., Jiang, Y., Luo, W., Zhang, J., et al. (2014). Linking brain electrical signals elicited by current outcomes with future risk decision-making. *Front. Behav. Neurosci.* 8:84. doi: 10.3389/fnbeh.2014.00084

Zhao, D., Gu, R., Tang, P., Yang, Q., and Luo, Y.-J. (2016). Incidental emotions influence risk preference and outcome evaluation. *Psychophysiology* 53, 1542–1551. doi: 10.1111/psyp.12694

Conflict of Interest Statement: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Psychology

ORIGINAL RESEARCH
published: 28 August 2019
doi: 10.3389/fpsyg.2019.01979

Neural Dynamics Underlying the Evaluation Process of Ambiguous Options During Reward-Related Decision-Making

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Specialty section:
This article was submitted to Decision Neuroscience, a section of the journal Frontiers in Psychology

Received: *03 May 2019*
Accepted: *13 August 2019*
Published: *28 August 2019*

Citation:
Zhu C, Pan J, Wang Y, Li J and Wang P (2019) Neural Dynamics Underlying the Evaluation Process of Ambiguous Options During Reward-Related Decision-Making. Front. Psychol. 10:1979. doi: 10.3389/fpsyg.2019.01979

Ambiguous decision-making involves different processes. However, few studies have focused on the evaluation process. In this study, event-related potentials (ERPs) and event-related spectrum perturbation (ERSP) techniques were used to explore the neural dynamics underlying the evaluation process of ambiguous options through an ambiguous choice task. Some important results emerged. We found a preference for lotteries with low ambiguity regardless of reward amount, suggesting that subjects were averse to ambiguity in our paradigm. Our electroencephalography (EEG) results clarified the neural dynamics underlying the evaluation process. In the time domain, lotteries with both a larger reward and lower ambiguity elicited a larger P3. In the time-frequency domain, larger amplitudes of delta activity at 200–400 ms and 500–600 ms post-stimulus were elicited by lotteries with low ambiguity. Moreover, lotteries with a larger reward elicited larger amplitudes of delta activity at 400–600 ms post-stimulus. Our ERPs and ERSP results suggested that individuals in our paradigm evaluated ambiguity and reward separately, and then integrated their evaluation to form subjective values of different lotteries.

Keywords: ambiguous options, evaluation, neural dynamics, P3, delta activity

INTRODUCTION

Decision-making under uncertainty permeates our daily life. According to the precise likelihood of outcome, economists divide two types of uncertain events: risk and ambiguity. For risk, the outcome probability corresponds to a point estimation. For ambiguity, the outcome probability is either unknown (Ellsberg, 1961) or an interval estimation (Becker and Brownson, 1964; Curley and Yates, 1985; Rustichini et al., 2005). The majority of uncertainty in real situations is ambiguity. In many experiments related to ambiguity, one of the most prominent phenomena, referred to as “ambiguity avoidance,” is the individual’s preference for risk over ambiguity (Ellsberg, 1961; Camerer and Weber, 1992). Decision-making is a continuous process, which entails the evaluation of ambiguous options, formation of preference, choice, and learning from feedback (Wang et al., 2015). Ambiguity avoidance has been demonstrated to emerge during the evaluation process (Rode et al., 1999). During the evaluation of ambiguous options, the mean outcome and its variance are integrated to form preference. Ambiguity is supposedly averse because of its high outcome variance. However, this speculation lacks support from neural dynamic evidence of the evaluation of ambiguous options.

The focus of previous neuroimaging studies has been on contrasting the neural mechanism related to decision-making under risk and ambiguity. Decision-making under ambiguity elicits greater activity in the amygdala, orbitofrontal cortex, lateral prefrontal cortex, anterior insular cortex, posterior inferior frontal gyrus, and posterior parietal cortex, and less activity in the striatum (Hsu et al., 2005; Huettel et al., 2006; Bach et al., 2009). One functional magnetic resonance imaging (fMRI) study investigated the neural representation of subjective value under risk and ambiguity (Levy et al., 2010). In that study, subjects were asked to make decisions under different levels of risk and ambiguity. Their behavioral data were used to calculate the subjective value of each option, and neural activity was measured. The results revealed that the activities of the striatum, medial prefrontal cortex, posterior cingulate cortex, and amygdala were correlated with the subjective value of risky and ambiguous options.

Event-related potentials (ERPs) and event-related spectral perturbations (ERSPs) have millisecond-level temporal resolution, which is useful in exploring the evaluation process of ambiguous options. Existing ERP studies have been mainly focused on neural correlates underlying the choice and feedback stage of decision-making under uncertainty (for reviews, see Chandrakumar et al., 2018). To our knowledge, only one ERP study has explored the neural mechanism underlying the evaluation stage (Wang et al., 2015). In their experiment, participants were asked to decide whether to bet or not, under ambiguity and risk. They made decisions after a random monetary reward was presented. They would either earn or lose the monetary reward if they decided to bet. Otherwise, they would earn nothing. The results revealed that a larger P3 was elicited by risky options compared with ambiguous options. Previous ERP studies have shed light on the neural dynamics of decision-making under ambiguity (Gu et al., 2010; Xu et al., 2011; West et al., 2014; Kóbor et al., 2015; Mussel et al., 2015; Wang et al., 2015; Endrass et al., 2016; Azcárraga-Guirola et al., 2017). However, there have been limitations. Decision-making under ambiguity includes several stages, from the evaluation of ambiguous options to feedback processing. Few ERP studies have been focused on the evaluation process. Although Wang et al. (2015) explored the neural dynamics underlying the evaluation of ambiguous options, they mainly aimed at comparing the neural mechanism of ambiguity and risk. Their paradigm did not allow one to distinguish between evaluation and choice processes. Moreover, their study did not clarify the temporal dynamics of ambiguous option evaluation, which entails processing of the level of ambiguity, reward amount, and the corresponding integration process.

In this study, we used ERPs and the ERSP technique to investigate neural temporal dynamics underlying the process of ambiguous option evaluation. Therefore, we developed an ambiguous choice task. Our task paradigm was derived from previous literature on risky choice (Wang et al., 2019), given that the evaluation of ambiguous options is somewhat similar to that of risky options (Levy et al., 2010). In our task, two ambiguous lotteries were serially presented. Subjects were then asked to choose one lottery to decide their payoff. This allowed us to separate evaluation and choice processes. No feedback was shown to the subjects to control for the learning effect. By varying the probability interval of reward, we manipulated the level of ambiguity, based on the methods of Levy et al. (2010). We set up four types of lotteries: high ambiguity with a reward of 20 Chinese yuan (CNY) (H20); high ambiguity with a reward of 10 CNY (H10); low ambiguity with a reward of 20 CNY (L20); and low ambiguity with a reward of 10 CNY (L10). For each reward, lotteries with different levels of ambiguity led to the same mean reward. Using this paradigm, we were able to clarify the integration process of ambiguity and mean reward during the evaluation of an ambiguous option.

Several electroencephalography (EEG) components in the time domain and time-frequency domain can be used to explore the process of ambiguous option evaluation. In the time domain, the relevant component during the evaluation stage is P3 (Goldstein et al., 2006; Broyd et al., 2012; Zhang et al., 2017; Zheng et al., 2017). The P3 peak at 300–600 ms post-stimulus at posterior scalp sites is associated with reward evaluation and anticipation (Pfabigan et al., 2015). Furthermore, P3 possibly encodes the subjective value of each ambiguous option. Thus, we hypothesized that both low ambiguity and reward of 20 CNY would elicit larger P3 amplitudes. In the time-frequency domain, delta power (1–4 Hz) is an index of reward processing (for review, see Knyazev, 2007, 2012). Therefore, the dynamics of delta activity when faced with four types of lotteries would reflect the sequential order of processing the ambiguity, mean reward, and integration between the two. We predicted that low ambiguity would elicit a larger delta band activity when processing the ambiguity, while the reward of 20 CNY would elicit a larger delta band activity when processing the mean reward. Moreover, we predicted that both low ambiguity and the reward of 20 CNY elicited larger delta band activity when processing the integration between ambiguity and mean reward.

MATERIALS AND METHODS

Participants

A total of 25 healthy volunteers (age range = 21–25 years; females = 12) from Nankai University participated in this study. Sample size was determined by power analysis. All participants were right-handed, native Chinese speakers. The participants had normal or corrected-to-normal vision and no history of psychiatric or neurological disorders. Each participant signed written informed consent forms and received a base payment of 30 Chinese yuan (CNY, roughly equal to US $4.50) for participation, plus a bonus of 0–60 CNY based on his/her decision. The study protocol was approved by the Ethics Committee of Nankai University. The procedures were performed in accordance with approved guidelines and the Declaration of Helsinki. Materials and data related to this study will be made available upon request.

Stimuli and Task

The participants performed an ambiguous choice task. In each trial, participants were presented with two lotteries sequentially with varying ambiguity levels and varying reward amounts.

Participants had to indicate which lottery they preferred. Each lottery appeared on the screen in the form of a "pie" painted partly red and partly green (**Figure 1**). All pies contained 10 sectors. Participants were told that each image on the screen represented a physical bag containing 10 balls. The relative numbers of red and green balls were indicated by the proportions of red and green sectors. Part of the pie was hidden by a gray occluder. The probability of drawing green or red balls was therefore ambiguous. Two different occluder sizes (covering either two or six sectors) represented two ambiguity levels. For the low ambiguity level, the probability of drawing a red ball could have been anywhere between 40 and 60%. Similarly, the probability of drawing a green ball could have been anywhere between those two values. For the high ambiguity level, the probability of drawing a red ball could have been anywhere between 20 and 80%. The probability of drawing a green ball could also have been anywhere between 20 and 80%. The number under the pie represented the amount of money to be won that was associated with the target color. For half of the participants, drawing a red ball yielded a given amount of money and drawing a green ball yielded nothing. For the other half of the participants, drawing a green ball yielded a given amount of money, and a red ball yielded nothing. Two reward amounts (10 and 20 CNY) were used at each ambiguity level, to give four types of lotteries, i.e., H20, H10, L20, and L10.

At the beginning of the experiment, participants were told that each lottery corresponded with a unique bag. Therefore, we provided four sealed bags associated with four types of lotteries. Before the task, participants were asked to sign their names on the sealed bags. This method was used to ensure the relative numbers of red and green balls could not have been adjusted by experimenters during the task. At the end of the experiment, three trials were randomly selected by computers. Based on the lotteries they chose in these trials, participants then drew a ball from each corresponding bag (if two or three lotteries were the same, they would draw a ball twice or three times from the corresponding bag with replacements). In addition to their participation fee, they were paid according to the lotteries and number of balls of the target color.

Procedure

The EEG recording was performed in a small, sound-attenuated, electrically shielded chamber. After the EEG electrodes were attached, the participants sat in a comfortable chair that was approximately 100 cm in front of a 23-inch (58.42 cm) computer monitor. Before the tasks began, all participants read the instructions carefully and were asked to take eight practice trials. **Figure 1** shows the timeline of a single trial. Each trial began with the presentation of a single centrally located white fixation cross for 600–800 ms. A black screen was then presented for 500–700 ms, followed by the first lottery for 1,000 ms. Subsequently, the second lottery was presented for 1,000 ms, after which, a black screen was presented for 500–700 ms. The order of these lotteries was counterbalanced. Thereafter, participants were asked to choose one of the lotteries to decide their payoff in that trial.

The entire experiment comprised 80 test and eight practice trials. Only the test trials were used for EEG analysis. The trials occurred within four blocks of 20 trials. Each block was separated by a break, the duration of which was determined by the participants. All 80 trials were performed within 15–25 min, during which the trials were randomly presented. The E-Prime software was used to control the display of stimuli and acquisition of behavioral data (Version 2.0, Psychology Software Tools, Inc.).

Electroencephalography Acquisition

The EEG data were recorded continuously with a 40-channel NuAmps DC amplifier (Compumedics Neuroscan, Inc., Charlotte, NC, USA). According to the International 10-20 System, 32 active Ag/AgCl electrodes were used. The EEG was sampled at 1,000 Hz using a 22-bit A/D converter. The reference and ground electrodes were positioned at AFz, and the impedances of all electrodes were kept below 10 kΩ.

Electroencephalography Analysis

Preprocessing of EEG data was performed with the EEGLAB 14.1.1 tool (Delorme and Makeig, 2004), implemented in MATLAB 2017a. In addition, a 0.1/30 Hz high-/low-pass filter was applied after the reference of EEG signals was reset to the average of the left and right mastoids. Individual epochs were extracted from −1,000 to 2,000 ms around the presentation of the stimulus defined as the lotteries that sequentially presented in our task. A manual artifact correction procedure was applied to eliminate trials with artifacts, based on visual inspection. Independent component analysis (ICA) was performed to remove eye movement, and the related ICA components were manually selected. Artifact-free epochs of each subject were grouped into four conditions, i.e., H20, H10, L20, and L10.

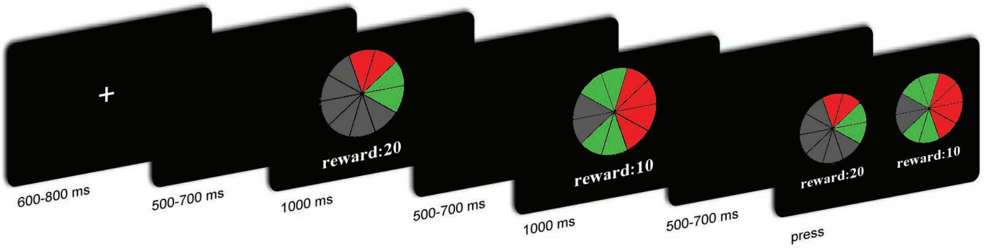

FIGURE 1 | Overview of the task and trial structure.

Clean EEG data were analyzed in the time domain. The 1,000-ms epochs were extracted, starting at 200 ms before the presentation of the stimulus. A 200-ms pre-stimulus period was used as baseline, and the accepted epochs were baseline-corrected. The P3 was scored as the mean voltage from 500 to 600 ms post-stimulus at Pz, corresponding to the 100-ms time window surrounding the peak.

Time-frequency analysis was performed using the Fieldtrip toolbox (Oostenveld et al., 2011) built-in ft_freqanalysis function, based on complex Morlet wavelet convolution (1–10 cycles, 1–30 Hz, 120 spaced frequencies, 1,000 time points per epoch). The time interval of −200 to 0 ms before presentation of the stimulus was used for baseline normalization. The mean converted amplitudes within 1–4 Hz from 200 to 300 ms, 300 to 400 ms, 400 to 500 ms, and 500 to 600 ms at Pz were used to analyze the delta band power change in different time windows.

For all analyses, the values of p were corrected using the Greenhouse-Geisser correction when the sphericity assumption was violated. A value of $p < 0.05$ was considered significant. Significant interaction was analyzed using the simple effect model. Statistics were analyzed using the SPSS 19.0 software.

RESULTS

Behavior Data

The subjective value of a lottery was defined as the frequency with which it was selected by the participants. The subjective value was analyzed using two-way repeated measures ANOVA (rmANOVA) with ambiguity levels (high vs. low) and reward amounts (10 vs. 20 CNY) as within-subject factors (**Figure 2A**). A significant main effect was found for reward amount [$F(1, 24) = 452.859$, $p < 0.001$, partial $\eta^2 = 0.950$], as a higher subjective value was noted for 20 CNY (mean ± SEM = 30.860 ± 1.392) versus 10 CNY (mean ± SEM = 9.140 ± 1.119). A significant main effect was also found for ambiguity [$F(1, 24) = 228.553$, $p < 0.001$, partial $\eta^2 = 0.905$], as a higher subjective value was noted for low ambiguity (mean ± SEM = 27.840 ± 1.808) versus high ambiguity (mean ± SEM = 12.160 ± 1.492). A significant interaction effect was revealed [$F(1, 24) = 15.600$, $p = 0.001$, partial $\eta^2 = 0.394$]. For high ambiguity, a significant main effect was observed with reward amount [$F(1, 24) = 210.251$, $p < 0.001$, partial $\eta^2 = 0.898$], as a higher subjective value was noted for 20 CNY (mean ± SEM = 21.760 ± 1.007) than 10 CNY (mean ± SEM = 2.560 ± 0.663). For low ambiguity, a significant main effect was also observed with reward amount [$F(1, 24) = 513.497$, $p < 0.001$, partial $\eta^2 = 0.955$], as a higher subjective value was observed for 20 CNY (mean ± SEM = 39.960 ± 0.040) than 10 CNY (mean ± SEM = 15.720 ± 1.053). For 20 CNY, a significant main effect was observed with ambiguity level [$F(1, 24) = 334.586$, $p < 0.001$, partial $\eta^2 = 0.933$], as a higher subjective value was noted for low ambiguity (mean ± SEM = 39.960 ± 0.040) than high ambiguity (mean ± SEM = 21.760 ± 1.007). For 10 CNY, a significant main effect was also observed with ambiguity level [$F(1, 24) = 87.662$, $p < 0.001$, partial $\eta^2 = 0.785$], as a higher subjective value was noted for low ambiguity (mean ± SEM = 15.720 ± 1.053) than high ambiguity (mean ± SEM = 2.560 ± 0.663).

Reaction time was analyzed using one-way rmANOVA with conditions (two lotteries with the same ambiguity level but different reward amounts vs. two lotteries with different ambiguity levels but same reward amount vs. two lotteries with different ambiguity levels and different reward amounts, henceforth referred to as SD vs. DS vs. DD). We found no significant main effects [$F(2, 48) = 1.818$, $p = 0.184$, partial $\eta^2 = 0.070$] for the various conditions (**Figure 2B**).

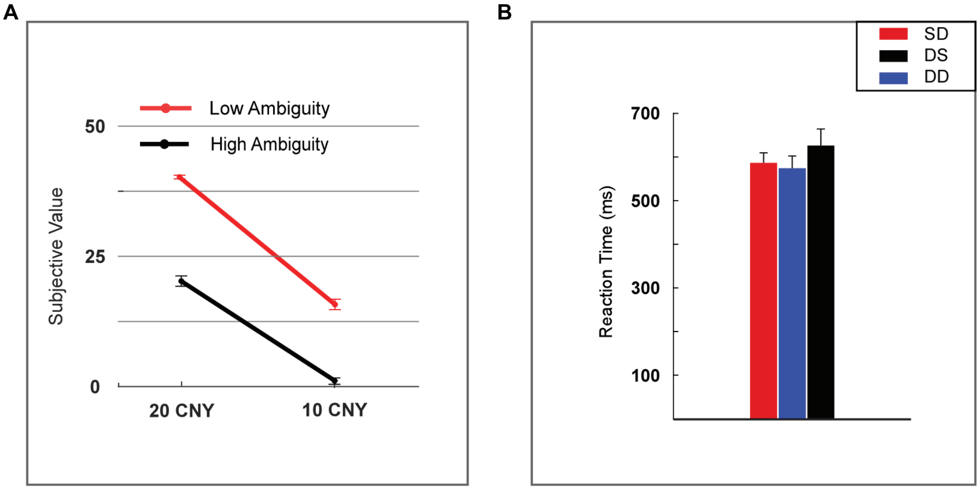

FIGURE 2 | Behavioral results. **(A)** Subjective value among lotteries (H20, H10, L20, and L10). **(B)** Reaction time among lotteries (H20, H10, L20, and L10). Error bars represent SEM. H20, high ambiguity with a reward of 20 CNY; H10, high ambiguity with a reward of 10 CNY; L20, low ambiguity with a reward of 20 CNY; L10, low ambiguity with a reward of 10 CNY. SD, two lotteries with same ambiguity level but different reward amounts; DS, two lotteries with different ambiguity levels but same reward amount; DD, two lotteries with different ambiguity levels and different reward amounts.

Electrophysiological Data

P3

A two-way rmANOVA was performed with ambiguity (high vs. low) and reward (10 vs. 20 CNY) as factors (**Figure 3**). A significant main effect was found [$F(1, 24) = 33.891$, $p < 0.001$, partial $\eta^2 = 0.585$] for reward amount, with a larger amplitude of P3 for 20 CNY (mean ± SEM = 2.730 ± 0.376 μV) than 10 CNY (mean ± SEM = 0.403 ± 0.417 μV). Moreover, a significant main effect was also found [$F(1, 24) = 12.367$, $p = 0.002$, partial $\eta^2 = 0.340$] for ambiguity level, with a larger amplitude of P3 for low ambiguity (mean ± SEM = 2.283 ± 0.430 μV) than high ambiguity (mean ± SEM = 0.824 ± 0.373 μV). However, no significant interaction effects were found.

Delta Activity

A two-way rmANOVA was performed on the delta power from 200 to 300 ms with ambiguity (high vs. low) and reward (10 vs. 20 CNY) as factors (**Figure 4**). Only one significant main effect was found [$F(1, 24) = 11.822$, $p = 0.002$, partial $\eta^2 = 0.330$] for ambiguity level, with a larger amplitude for low ambiguity (mean ± SEM = 2.379 ± 0.259 dB) than high ambiguity (mean ± SEM = 1.733 ± 0.218 dB). However, we found no significant main effects for reward or significant interaction effects.

A two-way rmANOVA was performed on the delta power from 300 to 400 ms with ambiguity (high vs. low) and reward (10 vs. 20 CNY) as factors (**Figure 5**). Only one significant main effect was found [$F(1, 24) = 7.646$, $p = 0.011$, partial $\eta^2 = 0.242$] for ambiguity, with a larger amplitude for low ambiguity (mean ± SEM = 2.444 ± 0.255 dB) than high ambiguity (mean ± SEM = 1.864 ± 0.219 dB).

A two-way rmANOVA was performed on the delta power from 400 to 500 ms with ambiguity (high vs. low) and reward (10 vs. 20 CNY) as factors (**Figure 6**). Only one significant main effect was found [$F(1, 24) = 9.846$, $p = 0.004$, partial $\eta^2 = 0.291$] for reward amount, with a larger amplitude for 20 CNY (mean ± SEM = 2.252 ± 0.200 dB) than 10 CNY (mean ± SEM = 1.502 ± 0.194 dB).

A two-way rmANOVA was performed on the delta power from 500 to 600 ms with ambiguity (high vs. low) and reward (10 vs. 20 CNY) as factors (**Figure 7**). A significant main

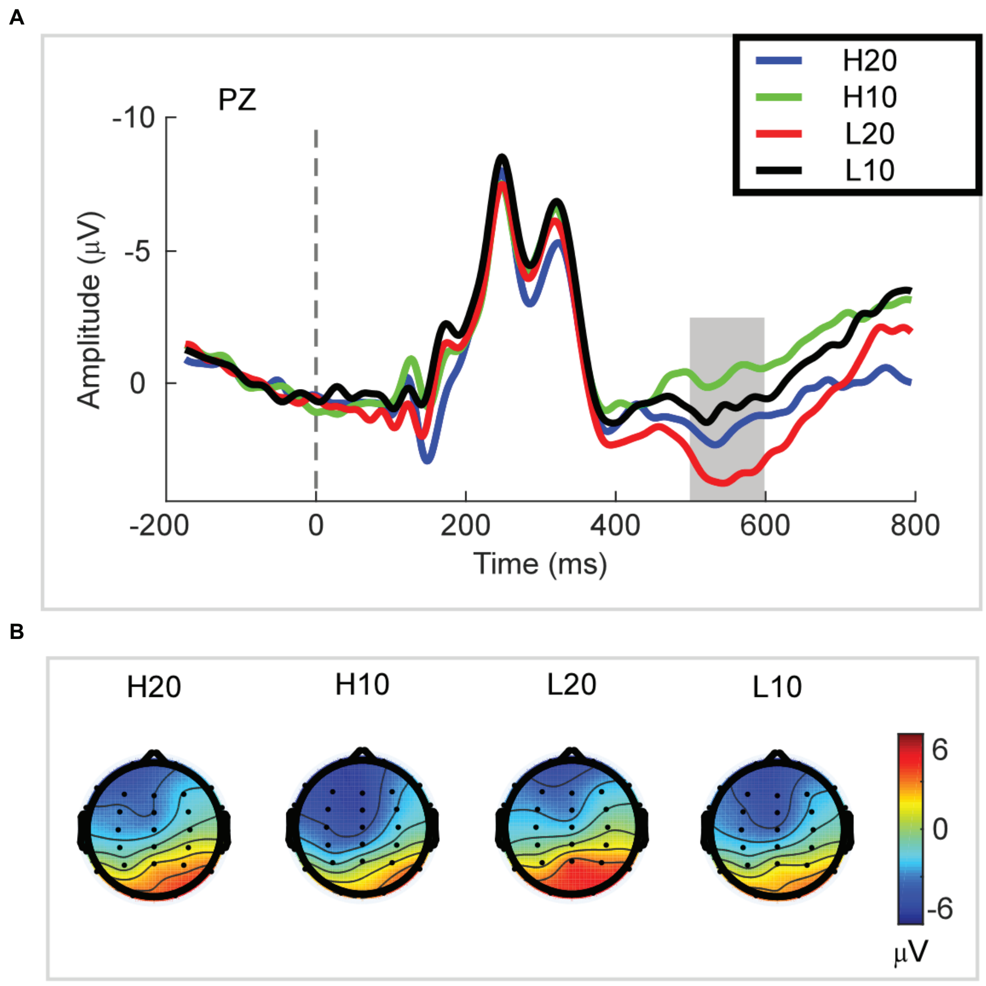

FIGURE 3 | P3 results. **(A)** Grand average ERP waves computed at Pz. **(B)** Topographic voltage maps of mean amplitude of the P3 wave.

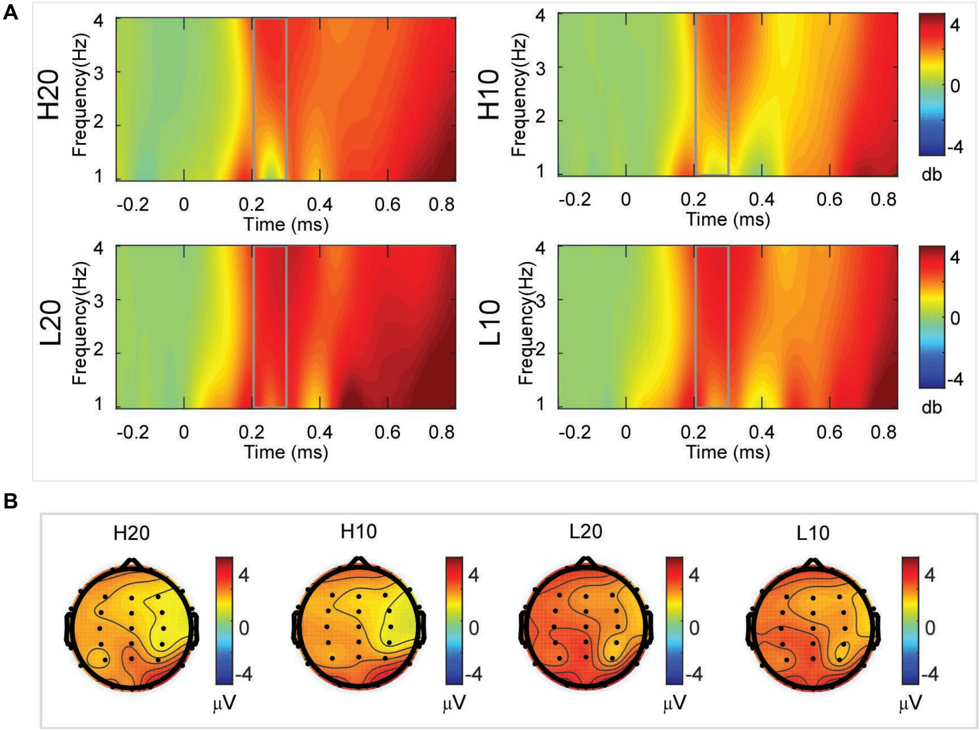

FIGURE 4 | Delta results from 200 to 300 ms. **(A)** Delta (1–4 Hz) activity at Pz. **(B)** Topographic maps of the mean amplitude of delta band power within 1–4 Hz from 200 to 300 ms.

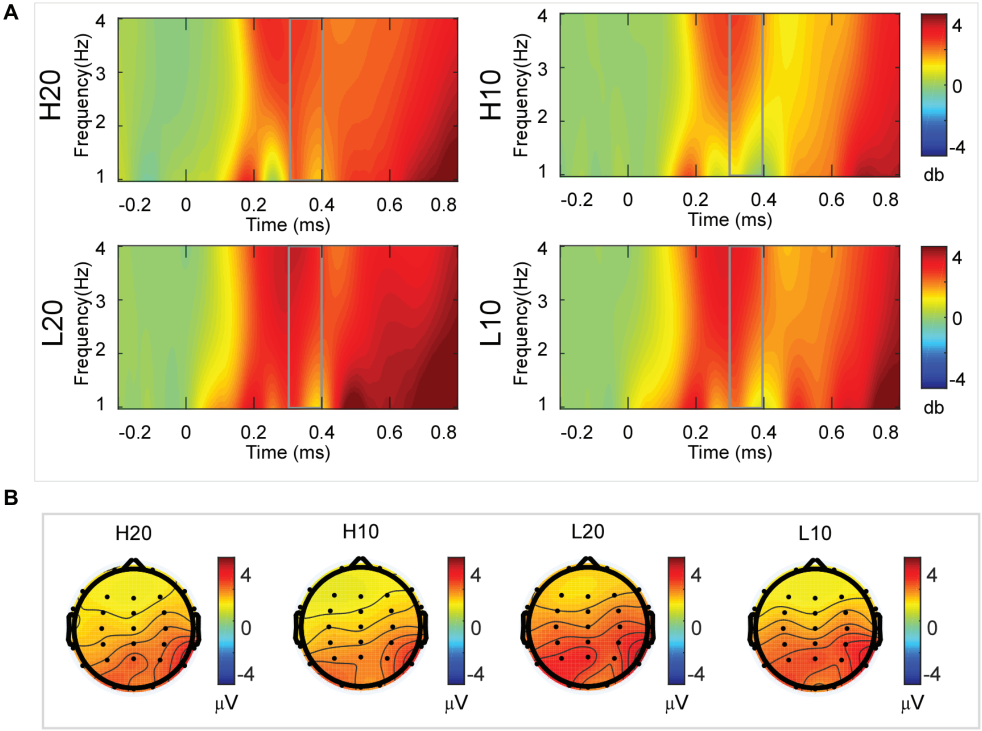

FIGURE 5 | Delta results from 300 to 400 ms. **(A)** Delta (1–4 Hz) activity at Pz. **(B)** Topographic maps of the mean amplitude of delta band power within 1–4 Hz from 300 to 400 ms.

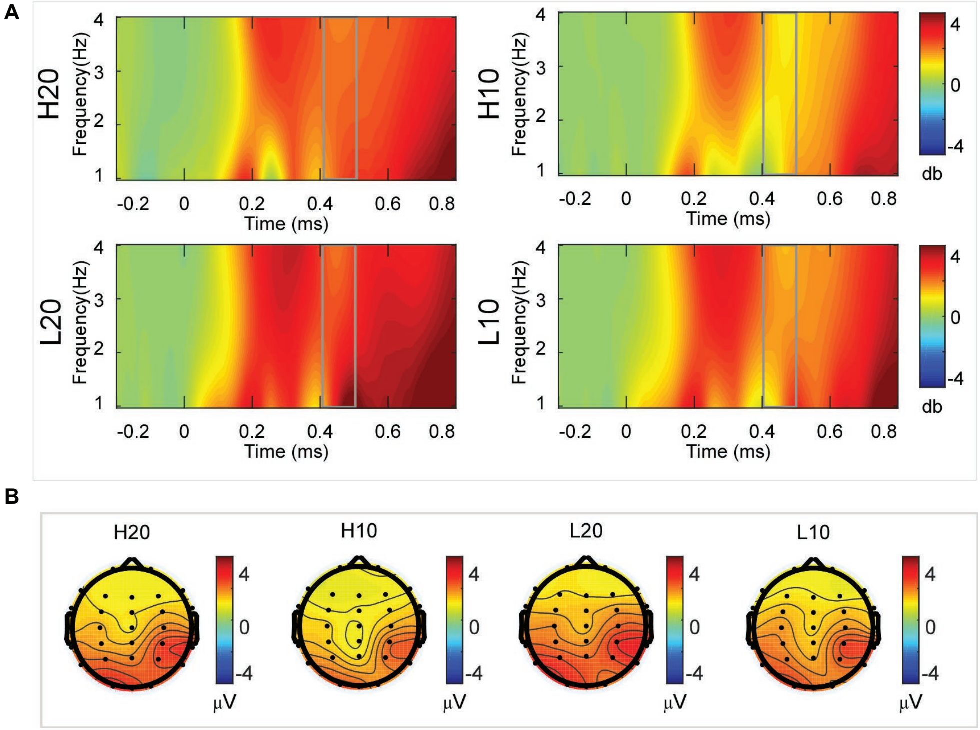

FIGURE 6 | Delta results from 400 to 500 ms. **(A)** Delta (1–4 Hz) activity at Pz. **(B)** Topographic maps of the mean amplitude of delta band power within 1–4 Hz from 400 to 500 ms.

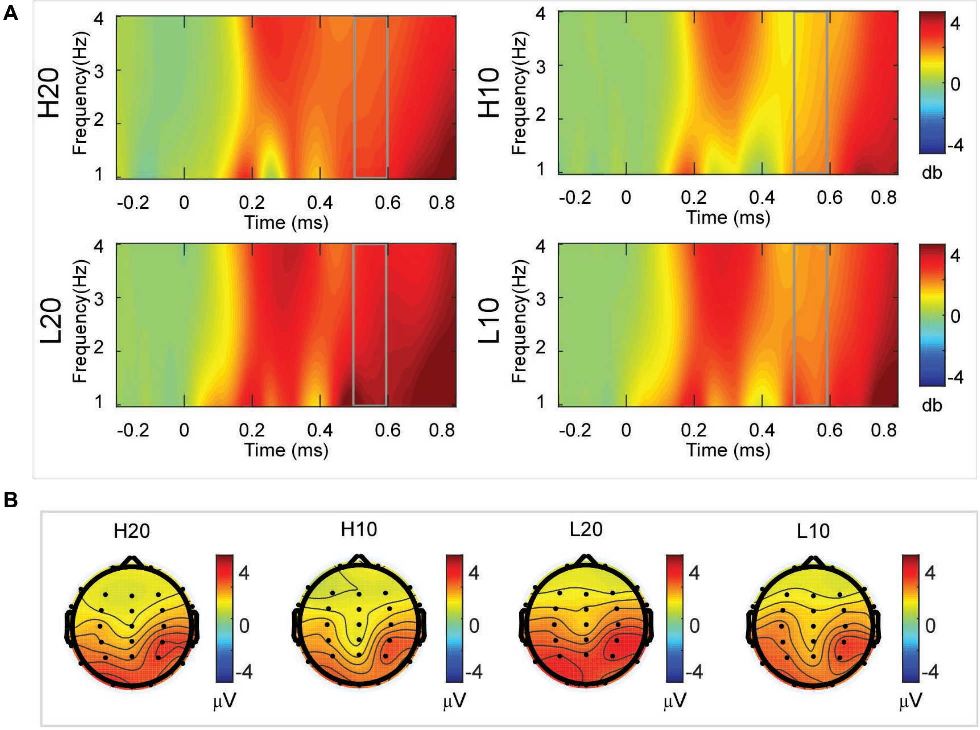

FIGURE 7 | Delta results from 500 to 600 ms. **(A)** Delta (1–4 Hz) activity at Pz. **(B)** Topographic maps of the mean amplitude of delta band power within 1–4 Hz from 500 to 600 ms.

effect was found [$F(1, 24) = 6.772$, $p = 0.016$, partial $\eta^2 = 0.220$] for ambiguity level, with a larger amplitude for low ambiguity (mean ± SEM = 2.485 ± 0.212 dB) than high ambiguity (mean ± SEM = 1.854 ± 0.160 dB). Moreover, a significant main effect was found [$F(1, 24) = 13.481$, $p = 0.001$, partial $\eta^2 = 0.360$] for reward, with a larger amplitude for 20 CNY (mean ± SEM = 2.658 ± 0.191 dB) than 10 CNY (mean ± SEM = 1.681 ± 0.199 dB). However, no significant interaction effects were found.

DISCUSSION

Ambiguous decision-making involves different processes, from evaluation to feedback. Previous behavioral studies have suggested that ambiguity aversion occurs because of a lower subjective value with high variance of the mean outcome during the evaluation process. However, this speculation lacks supportive evidence from neural dynamics analyses. In this study, ERP and ERSP techniques were used to explore the neural dynamics underlying the evaluation process of ambiguous options through an ambiguous choice task. Some important results have emerged. We found a preference for lotteries with low ambiguity regardless of reward amount, suggesting that subjects were averse to ambiguity in our paradigm. Our EEG results clarified the neural dynamics underlying the evaluation process. In the time domain, both lotteries with larger rewards and those with low ambiguity elicited a larger P3. In the time-frequency domain, larger amplitudes of delta activity at 200–400 and 500–600 ms post-stimulus were elicited by lotteries with low ambiguity. Moreover, lotteries with larger rewards elicited a larger amplitude of delta activity at 400–600 ms post-stimulus.

Our behavioral data showed that most participants disliked lotteries with high ambiguity and small rewards. This finding is consistent with previous studies regarding decision-making under ambiguity (Rode et al., 1999; Levy et al., 2010). In our task, the subjective value of lottery H10 was 2.56. When the ambiguity was low, the subjective value increased to 15.72. As the reward increased to 20 CNY, the subjective value increased significantly and reached 21.76 in cases of high ambiguity. Moreover, for lottery L20, the subjective value was 39.96 and significantly higher than all other lotteries. Lower ambiguity led to an increased frequency with which the lottery was chosen, and therefore, a larger subjective value. We noted that the reaction time was identical among different choice conditions (i.e., SD vs. DS vs. DD). This result suggested that the difficulty of choosing between different types of lotteries was similar in our task.

In the time domain, we observed an obvious P3 component peaking at approximately 500–600 ms following the presentation of the lotteries on the screen. This component reflects the stimulus categorization process (for reviews, see Polich, 2007) and motivational salience to the stimulus (for review, see Polich and Kok, 1995). The P3 wave has also been associated with activation of the ventral striatum (Pfabigan et al., 2015) during the evaluation process. Since the ventral striatum is a region related to reward processing (Delgado et al., 2000; Schultz, 2000; Breiter et al., 2001; Knutson et al., 2003; Tobler et al., 2007; Haber and Knutson, 2010; Kahnt et al., 2011; Sescousse et al., 2013, 2014; Wilson et al., 2018), the P3 can be an index of reward evaluation. In our study, both lotteries with low ambiguity and those with larger rewards elicited a larger amplitude of P3, indicating that P3 integrated the evaluation of ambiguity and reward. Among four types of lotteries, the amplitude of P3 for H10 was the smallest at only −0.215 μV. When the ambiguity was low, the amplitude of P3 increased to 1.022 μV. As the reward increased to 20 CNY, the amplitude of P3 increased and reached 1.863 μV in cases of high ambiguity. For the L20 lotteries, the amplitude of P3 was 3.543 μV, the highest among all lotteries. Considering our behavioral and ERP data together, we found that a larger amplitude of P3 led to an increased frequency with which a lottery was selected. Thus, we suggested that the amplitude of P3 during the evaluation process encoded the subjective value of each ambiguous lottery, and could be used to predict the subsequent choice.

In the time-frequency domain, delta activity is sensitive to reward evaluation during reward anticipation processing (for review, see Knyazev, 2007, 2012; Glazer et al., 2018). It could also be an index representing the integration of reward (Gheza et al., 2018; Zhu et al., 2019). In the present study, the dynamics of delta power for lotteries during the evaluation process reflected the subjects' processing of the elements of the lotteries (i.e., ambiguity level and mean reward) and their integration. At 200–400 ms after the stimulus, lotteries with low ambiguity elicited larger amplitudes of delta activity, indicating that individuals started to evaluate ambiguity at about 200 ms after the presentation of lotteries on the screen. This result also suggested that individuals preferred lotteries with low ambiguity to those with high ambiguity. During the next 100 ms, lotteries with a larger reward elicited larger amplitudes of delta activity, indicating that individuals evaluated reward at 400–500 ms post-stimulus. Moreover, this result suggested that individuals preferred larger rewards. At 500–600 ms post-stimulus, both lotteries with low ambiguity and those with larger rewards elicited larger amplitudes of delta activity. These results indicated that subjects integrated their evaluation of ambiguity and reward to form a subjective value of lotteries at 500–600 ms after presentation of the lotteries. This supports our findings in the time domain and supports the idea that delta activity plays a key role in P3 generation during reward evaluation (Demiralp et al., 2001; Bernat et al., 2007, 2015; Ergen et al., 2008; Ishii et al., 2009).

In summary, to our knowledge, this study is the first to investigate the neural dynamics underlying the evaluation process of lotteries under ambiguity. Our ERPs and ERSP results suggest that individuals in our paradigm evaluated ambiguity and reward separately. The ambiguity level was evaluated at 200–400 ms and the reward was evaluated at 400–500 ms after the lotteries were presented on the screen. At 500–600 ms after the stimulus, individuals integrated the evaluation of ambiguity and reward to form a subjective value of the different lotteries. These findings shed light on our understanding of the temporal course of processing ambiguous options. Furthermore, our findings provide neural dynamic evidence of the emergence of ambiguity avoidance during the evaluation process. One limitation of this study should be mentioned. Although the evaluation of ambiguity was earlier than that of reward in our task, whether individuals in other tasks evaluate ambiguity first is unclear. Future studies should explore the impacting factor of evaluation sequence during the process of ambiguous decision-making.

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 the Ethics Committee of Business of Nankai University committee 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 Business of Nankai University committee.

AUTHOR CONTRIBUTIONS

CZ, JP, PW, and JL designed the experiment. CZ and JP carried out the experiment, analyzed the data, wrote the paper, and contributed equally to this work. CZ, JP, JL, YW, and PW revised the paper.

FUNDING

This work was supported by the National Natural Science Fund of China (Grant numbers: 71673152; 71533002; 71602051); Ministry of Education in China Project of Humanities and Social Sciences (Grant number: 18JJD630001); The National Social Science Foundation of China (Grant number: 16BJY035); and Shandong Provincial Natural Science Fund, China (Grant number: ZR2016GM07).

REFERENCES

Azcárraga-Guirola, E., Rodríguez-Agudelo, Y., Velázquez-Cardoso, J., Rito-García, Y., and Solís-Vivanco, R. (2017). Electrophysiological correlates of decision making impairment in multiple sclerosis. *Eur. J. Neurosci.* 45, 321–329. doi: 10.1111/ejn.13465

Bach, D. R., Seymour, B., and Dolan, R. J. (2009). Neural activity associated with the passive prediction of ambiguity and risk for aversive events. *J. Neurosci.* 29, 1648–1656. doi: 10.1523/JNEUROSCI.4578-08.2009

Becker, S. W., and Brownson, F. O. (1964). What price ambiguity? Or the role of ambiguity in decision-making. *J. Polit. Econ.* 72, 62–73. doi: 10.1086/258854

Bernat, E. M., Malone, S. M., Williams, W. J., Patrick, C. J., and Iacono, W. G. (2007). Decomposing delta, theta, and alpha time–frequency ERP activity from a visual oddball task using PCA. *Int. J. Psychophysiol.* 64, 62–74. doi: 10.1016/j.ijpsycho.2006.07.015

Bernat, E. M., Nelson, L. D., and Baskin-Sommers, A. R. (2015). Time-frequency theta and delta measures index separable components of feedback processing in a gambling task. *Psychophysiology* 52, 626–637. doi: 10.1111/psyp.12390

Breiter, H. C., Aharon, I., Kahneman, D., Dale, A., and Shizgal, P. (2001). Functional imaging of neural responses to expectancy and experience of monetary gains and losses. *Neuron* 30, 619–639. doi: 10.1016/S0896-6273(01)00303-8

Broyd, S. J., Richards, H. J., Helps, S. K., Chronaki, G., Bamford, S., and Sonuga-Barke, E. J. (2012). An electrophysiological monetary incentive delay (e-MID) task: a way to decompose the different components of neural response to positive and negative monetary reinforcement. *J. Neurosci. Methods* 209, 40–49. doi: 10.1016/j.jneumeth.2012.05.015

Camerer, C., and Weber, M. (1992). Recent developments in modeling preferences: uncertainty and ambiguity. *J. Risk Uncertain.* 5, 325–370. doi: 10.1007/BF00122575

Chandrakumar, D., Feuerriegel, D., Bode, S., Grech, M., and Keage, H. A. (2018). Event-related potentials in relation to risk-taking: a systematic review. *Front. Behav. Neurosci.* 12:111. doi: 10.3389/fnbeh.2018.00111

Curley, S. P., and Yates, J. F. (1985). The center and range of the probability interval as factors affecting ambiguity preferences. *Organ. Behav. Hum. Decis. Process.* 36, 273–287. doi: 10.1016/0749-5978(85)90016-0

Delgado, M. R., Nystrom, L. E., Fissell, C., Noll, D. C., and Fiez, J. A. (2000). Tracking the hemodynamic responses to reward and punishment in the striatum. *J. Neurophysiol.* 84, 3072–3077. doi: 10.1152/jn.2000.84.6.3072

Delorme, A., and Makeig, S. (2004). EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *J. Neurosci. Methods* 134, 9–21. doi: 10.1016/j.jneumeth.2003.10.009

Demiralp, T., Ademoglu, A., Istefanopulos, Y., Başar-Eroglu, C., and Başar, E. (2001). Wavelet analysis of oddball P300. *Int. J. Psychophysiol.* 39, 221–227. doi: 10.1016/S0167-8760(00)00143-4

Ellsberg, D. (1961). Risk, ambiguity, and the savage axioms. *Q. J. Econ.* 75, 643–669. doi: 10.1017/cbo9780511609220.017

Endrass, T., Schuermann, B., Roepke, S., Kessler-Scheil, S., and Kathmann, N. (2016). Reduced risk avoidance and altered neural correlates of feedback processing in patients with borderline personality disorder. *Psychiatry Res.* 243, 14–22. doi: 10.1016/j.psychres.2016.06.016

Ergen, M., Marbach, S., Brand, A., Başar-Eroğlu, C., and Demiralp, T. (2008). P3 and delta band responses in visual oddball paradigm in schizophrenia. *Neurosci. Lett.* 440, 304–308. doi: 10.1016/j.neulet.2008.05.054

Gheza, D., De Raedt, R., Baeken, C., and Pourtois, G. (2018). Integration of reward with cost anticipation during performance monitoring revealed by ERPs and EEG spectral perturbations. *NeuroImage* 173, 153–164. doi: 10.1016/j.neuroimage.2018.02.049

Glazer, J. E., Kelley, N. J., Pornpattananangkul, N., Mittal, V. A., and Nusslock, R. (2018). Beyond the FRN: broadening the time-course of EEG and ERP components implicated in reward processing. *Int. J. Psychophysiol.* 132, 184–202. doi: 10.1016/j.ijpsycho.2018.02.002

Goldstein, R. Z., Cottone, L. A., Jia, Z., Maloney, T., Volkow, N. D., and Squires, N. K. (2006). The effect of graded monetary reward on cognitive event-related potentials and behavior in young healthy adults. *Int. J. Psychophysiol.* 62, 272–279. doi: 10.1016/j.ijpsycho.2006.05.006

Gu, R., Ge, Y., Jiang, Y., and Luo, Y. J. (2010). Anxiety and outcome evaluation: the good, the bad and the ambiguous. *Biol. Psychol.* 85, 200–206. doi: 10.1016/j.biopsycho.2010.07.001

Haber, S. N., and Knutson, B. (2010). The reward circuit: linking primate anatomy and human imaging. *Neuropsychopharmacology* 35, 4–26. doi: 10.1038/npp.2009.129

Hsu, M., Bhatt, M., Adolphs, R., Tranel, D., and Camerer, C. F. (2005). Neural systems responding to degrees of uncertainty in human decision-making. *Science* 310, 1680–1683. doi: 10.1126/science.1115327

Huettel, S. A., Stowe, C. J., Gordon, E. M., Warner, B. T., and Platt, M. L. (2006). Neural signatures of economic preferences for risk and ambiguity. *Neuron* 49, 765–775. doi: 10.1016/j.neuron.2006.01.024

Ishii, R., Canuet, L., Herdman, A., Gunji, A., Iwase, M., Takahashi, H., et al. (2009). Cortical oscillatory power changes during auditory oddball task revealed by spatially filtered magnetoencephalography. *Clin. Neurophysiol.* 120, 497–504. doi: 10.1016/j.clinph.2008.11.023

Kahnt, T., Heinzle, J., Park, S. Q., and Haynes, J. D. (2011). Decoding the formation of reward predictions across learning. *J. Neurosci.* 31, 14624–14630. doi: 10.1523/JNEUROSCI.3412-11.2011

Knutson, B., Fong, G. W., Bennett, S. M., Adams, C. M., and Hommer, D. (2003). A region of mesial prefrontal cortex tracks monetarily rewarding outcomes: characterization with rapid event-related fMRI. *NeuroImage* 18, 263–272. doi: 10.1016/S1053-8119(02)00057-5

Knyazev, G. G. (2007). Motivation, emotion, and their inhibitory control mirrored in brain oscillations. *Neurosci. Biobehav. Rev.* 31, 377–395. doi: 10.1016/j.neubiorev.2006.10.004

Knyazev, G. G. (2012). EEG delta oscillations as a correlate of basic homeostatic and motivational processes. *Neurosci. Biobehav. Rev.* 36, 677–695. doi: 10.1016/j.neubiorev.2011.10.002

Kóbor, A., Takács, Á., Janacsek, K., Németh, D., Honbolygó, F., and Csépe, V. (2015). Different strategies underlying uncertain decision making: higher executive performance is associated with enhanced feedback-related negativity. *Psychophysiology* 52, 367–377. doi: 10.1111/psyp.12331

Levy, I., Snell, J., Nelson, A. J., Rustichini, A., and Glimcher, P. W. (2010). Neural representation of subjective value under risk and ambiguity. *J. Neurophysiol.* 103, 1036–1047. doi: 10.1152/jn.00853.2009

Mussel, P., Reiter, A. M., Osinsky, R., and Hewig, J. (2015). State-and trait-greed, its impact on risky decision-making and underlying neural mechanisms. *Soc. Neurosci.* 10, 126–134. doi: 10.1080/17470919.2014.965340

Oostenveld, R., Fries, P., Maris, E., and Schoffelen, J. M. (2011). FieldTrip: open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. *Comput. Intell. Neurosci.* 2011:156869. doi: 10.1155/2011/156869

Pfabigan, D. M., Seidel, E. M., Paul, K., Grahl, A., Sailer, U., Lanzenberger, R., et al. (2015). Context-sensitivity of the feedback-related negativity for zero-value feedback outcomes. *Biol. Psychol.* 104, 184–192. doi: 10.1016/j.biopsycho.2014.12.007

Polich, J. (2007). Updating P300: an integrative theory of P3a and P3b. *Clin. Neurophysiol.* 118, 2128–2148. doi: 10.1016/j.clinph.2007.04.019

Polich, J., and Kok, A. (1995). Cognitive and biological determinants of P300: an integrative review. *Biol. Psychol.* 41, 103–146. doi: 10.1016/0301-0511(95)05130-9

Rode, C., Cosmides, L., Hell, W., and Tooby, J. (1999). When and why do people avoid unknown probabilities in decisions under uncertainty? Testing some predictions from optimal foraging theory. *Cognition* 72, 269–304. doi: 10.1016/S0010-0277(99)00041-4

Rustichini, A., Dickhaut, J., Ghirardato, P., Smith, K., and Pardo, J. V. (2005). A brain imaging study of the choice procedure. *Games Econ. Behav.* 52, 257–282. doi: 10.1016/j.geb.2004.08.005

Schultz, W. (2000). Multiple reward signals in the brain. *Nat. Rev. Neurosci.* 1, 199–207. doi: 10.1038/35044563

Sescousse, G., Caldú, X., Segura, B., and Dreher, J. C. (2013). Processing of primary and secondary rewards: a quantitative meta-analysis and review of human functional neuroimaging studies. *Neurosci. Biobehav. Rev.* 37, 681–696. doi: 10.1016/j.neubiorev.2013.02.002

Sescousse, G., Li, Y., and Dreher, J. C. (2014). A common currency for the computation of motivational values in the human striatum. *Soc. Cogn. Affect. Neurosci.* 10, 467–473. doi: 10.1093/scan/nsu074

Tobler, P. N., O'Doherty, J. P., Dolan, R. J., and Schultz, W. (2007). Reward value coding distinct from risk attitude-related uncertainty coding in human reward systems. *J. Neurophysiol.* 97, 1621–1632. doi: 10.1152/jn.00745.2006

Wang, G., Li, J., Wang, P., Zhu, C., Pan, J., and Li, S. (2019). Neural dynamics of processing probability weight and monetary magnitude in the evaluation of a risky reward. *Front. Psychol.* 10:554. doi: 10.3389/fpsyg.2019.00554

Wang, L., Zheng, J., Huang, S., and Sun, H. (2015). P300 and decision making under risk and ambiguity. *Comput. Intell. Neurosci.* 2015:108417. doi: 10.1155/2015/108417

West, R., Bailey, K., Anderson, S., and Kieffaber, P. D. (2014). Beyond the FN: a spatio-temporal analysis of the neural correlates of feedback processing in a virtual blackjack game. *Brain Cogn.* 86, 104–115. doi: 10.1016/j.bandc.2014.02.003

Wilson, R. P., Colizzi, M., Bossong, M. G., Allen, P., Kempton, M., and Bhattacharyya, S. (2018). The neural substrate of reward anticipation in health: a meta-analysis of fMRI findings in the monetary incentive delay task. *Neuropsychol. Rev.* 28, 496–506. doi: 10.1007/s11065-018-9385-5

Xu, Q., Shen, Q., Chen, P., Ma, Q., Sun, D., and Pan, Y. (2011). How an uncertain cue modulates subsequent monetary outcome evaluation: an ERP study. *Neurosci. Lett.* 505, 200–204. doi: 10.1016/j.neulet.2011.10.024

Zhang, Y., Li, Q., Wang, Z., Liu, X., and Zheng, Y. (2017). Temporal dynamics of reward anticipation in the human brain. *Biol. Psychol.* 128, 89–97. doi: 10.1016/j.biopsycho.2017.07.011

Zheng, Y., Li, Q., Zhang, Y., Li, Q., Shen, H., Gao, Q., et al. (2017). Reward processing in gain versus loss context: an ERP study. *Psychophysiology* 54, 1040–1053. doi: 10.1111/psyp.12855

Zhu, C., Pan, J., Li, S., Liu, X., Wang, P., and Li, J. (2019). Internal cost of spontaneous deception revealed by ERPs and EEG spectral perturbations. *Sci. Rep.* 9:5402. doi: 10.1038/s41598-019-41962-z

Conflict of Interest Statement: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Psychology

ORIGINAL RESEARCH
published: 19 September 2019
doi: 10.3389/fpsyg.2019.02124

Diminished Anticipatory and Consummatory Pleasure in Dysphoria: Evidence From an Experience Sampling Study

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Anhedonia, the experience of diminished pleasure, is a core feature of major depressive disorder and is often present long before the diagnosis of depression. Most previous studies have investigated anhedonia with self-report measures of trait anhedonia or with behavioral paradigms using laboratory stimuli, and the real-time characteristics of hedonic processing in subclinical depression remain under-investigated. We used the experience sampling method to evaluate momentary experience of hedonic feelings in the context of daily life. Dysphoric ($n = 49$) and non-dysphoric ($n = 51$) college students completed assessments of their current positive affect (PA), as well as state anticipatory and consummatory pleasure, 3 or 4 times a day every day for 2 weeks. The results showed that dysphoric individuals reported less state anticipatory and consummatory pleasure compared with non-dysphoric individuals. Moreover, significant time-lagged associations between anticipatory pleasure and follow-up consummatory pleasure were found in the whole sample, after adjustment for current PA. The current findings thus hold considerable promise in advancing our understanding of anhedonia as well as the important role of state anticipatory pleasure in relation to depression.

Keywords: anhedonia, anticipatory pleasure, consummatory pleasure, experience sampling, dysphoria

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Specialty section:
This article was submitted to
Decision Neuroscience,
a section of the journal
Frontiers in Psychology

Received: *13 June 2019*
Accepted: *02 September 2019*
Published: *19 September 2019*

Citation:
Li X, Zhang Y-T, Huang Z-J, Chen X-L, Yuan F-H and Sun X-J (2019) Diminished Anticipatory and Consummatory Pleasure in Dysphoria: Evidence From an Experience Sampling Study. Front. Psychol. 10:2124. doi: 10.3389/fpsyg.2019.02124

INTRODUCTION

Anhedonia, the diminished ability to experience pleasure, manifests as a transdiagnostic symptom among individuals with different psychiatric disorders (Thomsen et al., 2015). For this reason it has been identified by the Research Domain Criteria (RDoC) initiative as key to the investigation of behavioral and clinical symptoms across disorders (Insel et al., 2010). In the case of major depressive disorder (MDD), anhedonia is an essential diagnostic feature, and the severity of anhedonia has been found to correlate with the severity of depressive symptoms and time to remission (McMakin et al., 2012).

However, accumulating evidence suggests that anhedonia is not a unitary construct. Two independent sub-components of the hedonic processing function have been revealed: anticipatory pleasure and consummatory pleasure (Kring and Caponigro, 2010; Treadway and Zald, 2011). Anticipatory pleasure refers to pleasure derived from predicted future events; in contrast, consummatory pleasure involves the experience of pleasure during current events. The importance of such a distinction has been clear in other disorders. For example, anhedonia in schizophrenia has been demonstrated in anticipatory but not consummatory pleasure, in patients as well as in individuals at risk for schizophrenia (Li et al., 2015). More research is warranted to investigate the distinct roles of anticipatory and consummatory pleasure and their contributions to the pathology seen in depression.

Although it is well-documented that anhedonia plays a role in depression, the role of each type of anhedonia is not well-understood. Most empirical studies on anhedonia in depression have primarily focused on consummatory pleasure. Depressed individuals have been shown to report reduced emotional reactivity to stimuli used in laboratory research (Bylsma et al., 2008), and to demonstrate lower positive reactivity and elevated negative reactivity toward daily events (Bylsma et al., 2011). In addition, significant aberrations of brain function related to consummatory pleasure have been reported in individuals at risk for depression (Foti et al., 2011; Bress et al., 2012). In these studies reward-related brain areas such as the caudate, putamen, and anterior cingulate cortex were less activated in individuals with depression. Such blunted reactivity has also been detected in individuals at risk for depression (Saxena et al., 2017), suggesting that depression is robustly associated with reduced behavioral and neural hedonic responsivity, i.e., reduced consummatory pleasure.

Compared to consummatory pleasure, less is known about anticipatory pleasure in depression. A few studies have investigated anticipatory and consummatory pleasure simultaneously, and these studies have produced mixed findings. In an MDD sample, Sherdell et al. (2012) observed no deficits in reward seeking behavior or in consummatory responses to rewards in a laboratory based effort-reward task, suggesting intact anticipatory and consummatory hedonic processing capacity in depression. However, studies utilizing self-report measures of anhedonia have shown both blunted anticipatory and blunted consummatory pleasure in depression (Liu et al., 2012; Sherdell et al., 2012; Yang et al., 2014). Moreover, based on self-report, diminished anticipatory pleasure in depression, rather than consummatory pleasure, was found to be a significant predictor of effort expended for future rewards (Sherdell et al., 2012). Hence, both intact and reduced hedonic capacity have been found to relate to depression. One possible explanation for the differing results may have to do with the operationalization of anhedonia. Experimental studies evaluated dynamic hedonic responses on a trial-by-trial basis with laboratory-based task, while more static estimates of hedonic capacity were obtained with self-report measures.

Importantly, however, both the experimental method and self-report method have limitations in the study of anhedonia. On one hand, stimuli used in experimental studies (e.g., monetary rewards, positive images) are often standardized to obtain more precise control of confounding factors, but because contextual information is often removed or obscured, laboratory tasks might not be analogous to the actual changing contexts of everyday life. On the other hand, in self-report studies, participants are indicated to rate their pleasure experience in response to a hypothetical situation rather than actual situation. The self-report measures of hedonic experience rely heavily on retrospective recall and therefore scores derived from these measures might be confounded by the severity of memory deficits of the clinical sample characterized by anhedonia (Liu et al., 2012; Olsen et al., 2015). The reduced recall accuracy for specific personal memories has been suggested to be associated with reduced expectations for future events (Schacter et al., 2008). More critically, memory bias toward mood-congruent negative content is strongly related to depressive symptomatology and represents a primary mechanism in depression (Marchetti et al., 2018). Thus, retrospective reports might not provide a comprehensive representation of the fluctuating emotional experiences in daily life.

The experience sampling method (ESM) is a technique that enables real-time and repeated sampling, which could yield more reliable and accurate estimates than single-point assessment or retrospective reports (Csikszentmihalyi and Larson, 1987). Given the fact that emotional feelings are highly variable, the ESM is now generally considered as the "gold standard" to capture the dynamical signature of subjective experience (Shiffman et al., 2008). Important for the current study, the ESM has been frequently used to examine the daily fluctuations of affect in depression, with results showing that depression involves alteration in the mean level of both positive affect (PA) and negative affect (Kuppens et al., 2010; Thompson et al., 2012). The ESM makes it possible to examine how pleasure unfold in the context of daily life and thus offers insights into factors affect pathogenic processes and pathological states of depression.

Studies have started to employ ESM to investigate the temporal features of anticipatory and consummatory pleasure in the context of daily life. The first study was conducted in schizophrenia by Gard et al. (2007), in which deficits in anticipatory but not consummatory pleasure were reported, while recent ESM studies suggested intact capacity to experience pleasure during reward anticipation in schizophrenia (Gard et al., 2014; Edwards et al., 2018). However, the distinctive momentary feature of anticipatory and consummatory pleasure in relation to depression has rarely been studied. In a recent ESM study (Heininga et al., 2019), temporal consummatory pleasure of anhedonic individuals with current MDD episode was examined, the results showed that the frequency of reward experience in anhedonic individuals with current MDD episode were at equivalent levels as in healthy controls, suggesting intact consummatory pleasure in MDD with anhedonic symptoms. The first ESM study (Wu et al., 2017) investigating both daily anticipatory and consummatory pleasure of MDD, however, demonstrated that MDD patients reported blunted anticipatory and consummatory pleasure for daily activities. Although the accuracy of anticipatory ratings for pleasure could be estimated by subtracting consummatory ratings from anticipatory ratings in the Wu et al. (2017) study, this practice could not take full advantage of a key strength of ESM, which is the ability to capture the interactions between the two components of anhedonia. Cross-lagged regression models, on the other hand, could make use of the time-lagged structure of the data and thus could provide a better estimate of the moment-to-moment interplay between anticipatory ratings and consummatory ratings. The time-lagged analysis was utilized in present study to examine the extent to which anticipatory pleasure is related to in-the-moment experience of pleasure in the flow of daily life.

Although previous studies have provided preliminary evidence that patients with MDD had reduced daily experience of pleasure, it remains unknown whether these dysfunctions of hedonic processing emerge in dysphoria, who demonstrate elevated levels of depressive symptoms, but do not meet the diagnostic criteria for MDD. Dysphoric individuals showed impairment in cognitive function, such as working memory and interference control (Owens et al., 2012); and they reported more frequent use of non-adaptive emotional regulation strategies and experienced more negative affect than non-dysphoric individuals (Quigley and Dobson, 2014). Dysphoric individual are found to be at increased risk for developing MDD in the future (Gotlib et al., 1995), especially when dysphoria is present during young adulthood (Wilcox and Anthony, 2004). A recent ESM study provided preliminary evidence for blunted consummatory pleasure in individuals with anhedonia (Heininga et al., 2017). The temporal unfolding of anticipatory pleasure and the predictive relationship between anticipatory and consummatory pleasure in dysphoria, however, have not been fully studied. Given the close relationship between dysphoria and depression, we speculate that diminished anticipatory and consummatory pleasure might be observed in people with dysphoria.

In the affect literature, pleasure has been considered a dimension of PA. Research investigating the characteristics of PA in depression has suggested that depressive symptoms are related to lower PA both in clinical (Thompson et al., 2012) and non-clinical samples (van Roekel et al., 2016), while the functioning of PA in anhedonia is not yet fully understood. Most experimental studies have examined pleasure ratings in response to stimuli without considering the affective context, especially PA. The dynamic interaction of PA, negative affect and stress experience differed between anhedonic and non-anhedonic individuals with subclinical depression (Bos et al., 2018), suggesting an interplay between anhedonia and temporal affective experience. Our study extends the prior research by considering the impact of PA on the anticipatory and consummatory components of the experience of pleasure in dysphoria.

The primary goal of the current study was to understand the nature of anticipatory and consummatory pleasure in individuals with dysphoria in college-age population by using ESM. By studying individuals at risk for depression, mechanisms that underlie the future development of MDD episode may be uncovered. Furthermore, the recruitment of dysphoric individuals could overcome some of the confounding factors when studying patients with MDD, such as medication, severity of illness and episode number. MDD has its peak incidence in young adults (Kessler et al., 2003), thus a focus of college-age sample is of great relevance. Trait dispositions in anticipatory and consummatory pleasure were assessed with questionnaires. Other data were collected using ESM. Specifically, all participants provided ratings of temporal PA, anticipatory pleasure, and consummatory pleasure in response to phone prompts 3 to 4 times a day for 14 days. It was hypothesized that dysphoric individuals would report less PA, as well as less state anticipatory and consummatory pleasure. Moreover, we explored the potential role of anticipation of pleasure in predicting current pleasure, and whether this relationship varied between individuals with and without dysphoria. Because few studies have examined the predictive relationship between anticipatory and consummatory pleasure, no hypothesis was made regarding group difference, and the relationship between anticipatory pleasure and current pleasure was examined separately in each group. This study also examined the extent to which PA influences the experience of pleasure, and whether PA changes the relationship between anticipatory pleasure and consummatory pleasure. Finally, exploratory analyses of group differences on these time-lagged associations between dysphoric and non-dysphoric groups were performed.

MATERIALS AND METHODS

Participants

Three hundred and forty-one college students from Wuhan, China were invited to complete the Beck Depression Inventory-II (BDI-II, Beck et al., 1996), which taps into the severity of depressive symptomology in the general population. The BDI-II is currently one of the most widely used measure for assessing depression, and it has been shown to have good sensitivity and specificity in screening MDD in college-student population (Shean and Baldwin, 2008). Participants who scored 20 (moderate depression) or higher were identified as dysphoric individuals, and participants who scored lower than 14 (minimal depression) were classified as non-dysphoric controls, the BDI-II cut-off for dysphoric and non-dysphoric individuals was consistent with previous studies with college-student sample (Lissnyder and Koster, 2010; Owens et al., 2012; Quigley and Dobson, 2014). Potential participants who met either of these cut-off criteria on the BDI-II were screened by phone to check for availability to participate in the experience sampling study. Based on the phone interview, individuals with a history of psychiatric disorders, brain injury, or substance abuse were not included. As a result, 51 dysphoric individuals and 56 non-dysphoric controls were included in the present study. After baseline assessment, two participants from the dysphoric group and three from the non-dysphoric control group dropped out due to scheduling problems.

This study was approved by the Ethics Committee of the Central China Normal University. Written informed consent was obtained from all participants at the beginning of the baseline assessment. Participants were told they could stop participating at any time without penalty. At the end of the study participants received compensation of 30 RMB.

Baseline Assessment

On the first day they arrived at our laboratory, participants were administered two self-report measures. The Temporal Experience of Pleasure Scale (TEPS, Gard et al., 2006) is a self-report measure that assesses the trait dispositions of anticipatory pleasure and consummatory pleasure. The Chinese version of the TEPS (Chan et al., 2012) contains 20 items and participants answered each item on a 6-point Likert scale ranging from 1 (“very false for me”) to 6 (“very true for me”). Higher scores indicate greater hedonic capacity. Cronbach’s α was 0.759 for the whole scale, 0.726 for the consummatory pleasure subscale, and 0.530 for the anticipatory pleasure subscale. The Snaith–Hamilton Pleasure Scale (SHAPS), developed by Snaith et al. (1995), is a self-rating scale used to measure trait consummatory pleasure in certain situations. Each item is rated on a four-point Likert scale from 1 (“definitely agree”) to 4 (“definitely disagree”). The SHAPS contains 14 items, and higher scores indicate more severe deficits in consummatory pleasure. The Chinese version of the SHAPS has good internal consistency (Liu et al., 2012). Cronbach’s α in the present study was 0.891.

ESM Procedure

An Internet link containing the set of ESM assessments was sent to each participant’s smart phone 3–4 times each day between 8:00 a.m. to 10:00 p.m., with a time interval of more than 90 min between two adjacent points, for 14 consecutive days. This resulted in a maximum of 56 events per person. Participants were asked to complete the brief assessments as soon as they received the link on their smartphone. If no response was given within 30 min or the participant spent more than 180 s to complete the assessments, the data were considered missing. Two participants from the non-dysphoric group were removed from the final analysis because their response rates were lower than 50%. Thus the final sample consisted of 49 participants in the dysphoric group and 51 participants in the non-dysphoric group. No significant group differences were observed in gender, age, or education (**Table 1**).

Momentary PA

Momentary PA was measured with the 10 positive items (alert, excited, enthusiastic, attentive, proud, inspired, interested, determined, strong, active) from the Positive and Negative Affect Schedule (PANAS; Watson et al., 1988) using the structure “At this moment I feel...” For each item, participants were asked to indicate the extent to which they were experiencing a certain affect at that moment, from 1 (“not at all”) to 5 (“very much”).

TABLE 1 | Sample characteristics.

	Dysphoric group (*n* = 49)	**Non-dysphoric group (*n* = 51)**	***t*/χ2**	***p***
	(*M* ± *SD*)	**(*M* ± *SD*)**		
Age	20.22 ± 1.37	20.78 ± 1.74	1.79	0.08
Gender (% female)	85.71	82.35	0.21	0.79
Education (years)	14.20 ± 1.14	14.75 ± 1.56	1.99	0.50
BDI-II	24.78 ± 4.91	7.73 ± 3.67	19.72	<0.01
TEPS_total	82.39 ± 12.86	85.73 ± 9.29	1.49	0.14
Anticipatory pleasure	37.45 ± 6.64	39.12 ± 4.43	1.47	0.15
Consummatory pleasure	44.94 ± 7.61	46.61 ± 6.55	1.18	0.24
SHAPS	21.47 ± 6.32	20.73 ± 5.17	0.65	0.52

BDI-II, Beck Depression Inventory-II; TEPS, The Temporal Experience of Pleasure Scale; SHAPS, The Snaith–Hamilton Pleasure Scale.

State Anticipatory Pleasure and Consummatory Pleasure

To assess consummatory pleasure, participants firstly were asked to indicate what they were doing at that moment, by selecting from several options (i.e., work/study, sleeping, eating, daydreaming, cleaning, playing video games, interacting on social media, shopping, watching movies, going on a date, group discussion, other) and then to rate the amount of pleasure they were experiencing from 1 (“none”) to 10 (“an extremely large amount”) on a visual analog scale. To measure anticipatory pleasure at the state level, participants were asked to indicate what kind of activity they would be involved in next, and then they were asked to forecast the amount of enjoyment they would derive from that activity from 1 (“none”) to 10 (“an extremely large amount”). By including questions regarding current and future activities, the design helps to ensure that ratings for consummatory pleasure and anticipatory pleasure were based on daily events rather than memory representations. The use of brief measures is common in ESM research because excessive length can compromise response quality and reduce compliance (Bakker et al., 2017; Starr and Hershenberg, 2017; Edwards et al., 2018).

Data Analysis

Group differences on demographic information and baseline self-report measures were analyzed with SPSS 23.0. The ESM data have a hierarchical structure in which within-person daily observations (Level 1; e.g., state experience of pleasure) are nested within between-person characteristics (Level 2; e.g., dysphoric status). Therefore, data were analyzed by means of multilevel modeling in Mplus version 7.4. Separate models were estimated for daily PA, state anticipatory pleasure, and state consummatory pleasure. Furthermore, all Level 1 predictors were person-mean centered (i.e., around each participant’s mean score) to separate within-person effects from between-person effects (Finch and Bolin, 2017, pp 38–39). Intercepts and slopes of level 1 were modeled as random effects, allowing the intercepts and slopes to vary at between-person level (i.e., level 2) (Nezlek, 2012).

Before running models to test our hypotheses, we first ran null models in Mplus (i.e., containing no predictors at any level) with PA, state anticipatory pleasure and state consummatory pleasure as the outcome variables. This type of analysis can be used to calculate intraclass correlation coefficients (ICCs), which provides an estimate of the proportion of variance in the outcome variable accounted for by the between-person level, which reflects individual differences (vs. the within-person level, which reflects situational differences).

Associations Between Momentary Pleasure and Dysphoric Status

To examine whether dysphoric status predicted differences in anticipatory and consummatory pleasure across daily observations, we regressed the within-person parameters on dysphoric status (i.e., 0 = non-dysphoric group; 1 = dysphoric group) (see section "Model 1").

Model 1

Level 1: PA_{ij} or anticipatory pleasure $_{ij}$ or consummatory pleasure $_{ij} = \beta_{0j} + r_{ij}$

Level 2: $\beta_{0j} = \gamma_{00} + \gamma_{01}$ (dysphoric status $_j$) $+ U_{0j}$

In the equations, *i* represents time point, and *j* represents person. The outcome at Level 1 (e.g., PA), representing the observed score of person *j*'s at time *i*, was modeled as a function of a random intercept (β_{0j}) representing the within-person mean of the corresponding outcome variable, r_{ij} represents residual errors at within-person level. At Level-2, γ_{00} represents mean pleasure for the non-dysphoric group, and γ_{01} represents the difference in mean pleasure between the dysphoric and non-dysphoric groups. U_{0j} represents residual errors at between-person level.

Next, to reveal the unique associations between momentary pleasure and dysphoria, we reran the full models, controlling for PA (see section "Model 2").

Model 2

Level 1: consummatory pleasure $_{ij}$ or anticipatory pleasure $_{ij} = \beta_{0j} + \beta_{1j}\,\text{PA}_{ij} + r_{ij}$

Level 2: $\beta_{0j} = \gamma_{00} + \gamma_{01}$ (dysphoric status $_j$) $+ U_{0j}$

$\beta_{1j} = \gamma_{10} + \gamma_{11}$ (dysphoric status $_j$) $+ U_{1j}$

The outcome at Level 1 (e.g., consummatory pleasure), representing the observed score of person *j*'s score at time *i*, was modeled as a function of a random intercept (β_{0j}) representing the mean pleasure of person *j*, and a random slope (β_{1j}) representing the relationship between a person *j*'s PA at time *t* and consummatory pleasure at time *t*.γ_{00} and γ_{10} represent the average (or fixed-effects) estimates of consummatory pleasure and PA of the non-dysphoric group, while γ_{01} and γ_{11} represent group differences of consummatory pleasure and PA between the dysphoric and non-dysphoric groups.

Concordance Between Anticipatory and Consummatory Pleasure

Finally, to investigate how much the anticipated pleasure for an activity is concordant with the amount of consummatory pleasure, time-lagged associations between anticipatory pleasure and consummatory pleasure were estimated with an autocorrelation approach. In particular, we conducted multilevel modeling to predict consummatory pleasure at sampling moment *t* from anticipatory pleasure at *t*-1 (see section "Model 3"). Additionally, consummatory pleasure at *t*-1 and PA at *t* were included as covariates separately (see sections "Model 4, 5") and simultaneously (see section "Model 6") to control for potential confounding effects. Moreover, to examine whether dysphoria moderate these associations, a group variable indicating dysphoric status was added as the Level 2 predictor to test for group differences between the dysphoric and non-dysphoric groups (see **Supplementary Materials** for Model equations and further details).

Model 3

Level 1: consummatory pleasure $_{ij} = \beta_{0j} + \beta_{1j}$ (anticipatory pleasure $_{t-1}$) $+ r_{ij}$

Level 2: $\beta_{0j} = \gamma_{00} + U_{0j}$

$\beta_{1j} = \gamma_{10} + U_{1j}$

Model 4

Level 1: consummatory pleasure $_{ij} = \beta_{0j} + \beta_{1j}$ (anticipatory pleasure $_{t-1}$) $+ \beta_{2j}$ (consummatory pleasure $_{t-1}$) $+ r_{ij}$

Level 2: $\beta_{0j} = \gamma_{00} + U_{0j}$

$\beta_{1j} = \gamma_{10} + U_{1j}$

$\beta_{2j} = \gamma_{20} + U_{2j}$

Model 5

Level 1: consummatory pleasure $_{ij} = \beta_{0j} + \beta_{1j}$ (anticipatory pleasure $_{t-1}$) $+ \beta_{2j}$ (PA $_t$) $+ r_{ij}$

Level 2: $\beta_{0j} = \gamma_{00} + U_{0j}$

$\beta_{1j} = \gamma_{10} + U_{1j}$

$\beta_{2j} = \gamma_{20} + U_{2j}$

Model 6

Level 1: consummatory pleasure $_{ij} = \beta_{0j} + \beta_{1j}$ (anticipatory pleasure $_{t-1}$) $+ \beta_{2j}$ (consummatory pleasure $_{t-1}$) $+ \beta_{3j}$ (PA $_t$) $+ r_{ij}$

Level 2: $\beta_{0j} = \gamma_{00} + U_{0j}$

$\beta_{1j} = \gamma_{10} + U_{1j}$

$\beta_{2j} = \gamma_{20} + U_{2j}$

$\beta_{3j} = \gamma_{30} + U_{3j}$

In the equations, the outcome at Level 1 (consummatory pleasure_{ij}), representing a person *j*'s score on consummatory pleasure items at time *i*, was modeled as a function of a random intercept (β_{0j}) and random slopes (β_{1j}, β_{2j}, β_{3j}). β_{0j} represents person *j*'s mean score for consummatory pleasure *t*; β_{1j} represents the relationship between a person *j*'s anticipatory pleasure at time *t*-1 and consummatory pleasure at time *t*; β_{2j} represents the relationship between person *j*'s current consummatory pleasure and their consummatory pleasure at the prior time point in Model 4 (current PA in Model 5). β_{3j} represents the relationship between person *j*'s current consummatory pleasure and current PA. r_{ij} represents residual errors at within-person level.

The Level-2 parameter estimates (γ_{00}, γ_{10}, γ_{20}, γ_{30}) represent the average (or fixed-effects) estimates across participants. U_{0j}, U_{1j}, U_{2j}, and U_{3j} represent residual errors at between-person level.

RESULTS

Self-Report Measures

There were no significant group differences between the dysphoric and non-dysphoric group on the TEPS total score, $t(98) = 1.49$, $p = 0.14$, anticipatory pleasure subscale, $t(83.25) = 1.47$, $p = 0.15$, or consummatory pleasure subscale, $t(98) = 1.18$, $p = 0.24$. Moreover, no significant group difference was observed on the SHAPS total score, $t(98) = 0.65$, $p = 0.52$. These results suggested that the dysphoric group demonstrated no attenuation of trait anticipatory or consummatory pleasure.

ESM Estimates of State Anticipatory and Consummatory Pleasure

To determine whether age, gender, education, and time of assessments covaried with our dependent variables, we regressed these variables on consummatory pleasure$_{ij}$, anticipatory pleasure$_{ij}$, and PA$_{ij}$ separately. Results showed that those dependent variables did not vary by age, gender, education, or time. Thus, these demographic variables and time were not included as covariates in further analyses.

The ICCs from the null models revealed that 39.9% of the variance in PA, 34.9% of the variance in state anticipatory pleasure and 39.4% of the variance in state consummatory pleasure was at the between-person level, suggesting that both the temporal situation and dysphoric status play a role in momentary PA and the experience of pleasure in daily life. Several multilevel models were tested to examine the distinct contribution of dysphoric status to momentary pleasure respectively.

No significant group difference was observed in PA between the dysphoric and non-dysphoric groups ($p = 0.64$). However, individuals in the dysphoric group reported lower levels of state anticipatory pleasure ($\beta = -0.77$, $SE = 0.23$, $p < 0.01$) and consummatory pleasure ($\beta = -0.82$, $SE = 0.23$, $p < 0.01$) than individuals in the non-dysphoric group. Moreover, group differences between the dysphoric and non-dysphoric group in state anticipatory and consummatory pleasure remained statistically significant after including PA as a covariate (**Table 2**).

Impact of Anticipatory Pleasure on Consummatory Pleasure

Results of tests of Models 3–6, namely time-lagged analyses examining associations between anticipatory pleasure and changes in consummatory pleasure in the dysphoric and non-dysphoric groups separately, are presented in **Table 3**. Model 3 tested consummatory pleasure at the current moment as a function of anticipated pleasure at the prior time point. We found that greater anticipatory pleasure was a significant predictor of greater follow-up consummatory pleasure in the dysphoric group ($\beta = 0.15$, $SE = 0.04$, $p < 0.01$), but not the non-dysphoric group ($\beta = 0.05$, $SE = 0.04$, $p = 0.22$). In addition, the significant association between anticipatory pleasure at t-1 and consummatory at t in the dysphoric group remained unchanged after controlling for consummatory pleasure $_{t-1}$ (Model 4), PA $_{t}$ (Model 5), or both of them (Model 6), all $ps < 0.01$. In the non-dysphoric group, no significant relationship was found between anticipatory pleasure and consummatory pleasure, all ps > 0.05.

TABLE 2 | Estimates of positive affect (PA), anticipatory and consummatory pleasure in individuals with dysphoria compared with non-dysphoric individuals.

	Outcome variable	Covariate	β	*SE*	*p*
Model 1					
	PA	-	0.13	0.29	0.64
	Anticipatory pleasure	-	−0.77	0.23	<0.01
	Consummatory pleasure	-	−0.82	0.23	<0.01
Model 2					
	Anticipatory pleasure		−0.77	0.23	<0.01
		PA	0.18	0.19	0.35
	Consummatory pleasure		−0.82	0.23	<0.01
		PA	0.36	0.20	0.08

The moderating effects of dysphoria on these associations were not significant (all ps > 0.05, see **Supplementary Table S1**). Therefore, we rerun the models 3–6 by including all participants to determine if the predictive relationships between anticipatory pleasure and consummatory pleasure were statistically significant in the whole sample. The results showed that anticipatory pleasure alone positively predict current levels of consummatory pleasure at the trend level, $\beta = 0.08$, $SE = 0.04$, $p = 0.07$; after controlling for current PA, a significant association was found between anticipatory pleasure at t-1 and consummatory at t, $\beta = 0.04$, $SE = 0.02$, $p = 0.02$. In addition, the association between current PA and consummatory pleasure was also significant, $p < 0.01$, indicating that a higher level of anticipatory pleasure at prior time point in conjunction with higher current PA are associated with greater experience of consummatory pleasure for all participants.

DISCUSSION

The aim of this study was to investigate state anhedonia in subclinical depression, taking into account trait anhedonia and current PA. ESM was utilized to track the momentary experience of anticipatory and consummatory pleasure over the course of 14 consecutive days in dysphoric and non-dysphoric individuals. Multilevel analyses showed that compared to the non-dysphoric individuals, the dysphoric individuals showed less pleasure during the anticipation of future events and the engagement of on-going activities, and this pattern remained unchanged after adding temporal PA as a covariate. However, no group differences between dysphoric and non-dysphoric individuals were observed regarding trait anhedonia. Moreover, a significant predictive relationship between state anticipatory and consummatory pleasure after adjustment for temporal PA was revealed in the whole sample. Investigating the distinct nature of anticipatory and consummatory pleasure in daily life may help us to understand the mixed findings of prior studies on anhedonia in depression.

Consistent with our hypothesis, dysphoric individuals, compared to non-dysphoric individuals, reported lower levels of pleasure during anticipation of an upcoming event. This finding is consistent with experimental studies investigating anticipatory responses to laboratory stimuli in MDD (McFarland and Klein, 2009; Admon and Pizzagalli, 2015) and in dysphoria (Yuan and Kring, 2009). For example, in the study of McFarland and Klein (2009), compared to healthy controls, patients with MDD reported less PA when anticipating monetary reward. Similarly, neuroimaging studies have found blunted response during anticipation at the ventral striatum, a core region involved in reward processing, both in patients with MDD (Arrondo et al., 2015; Keren et al., 2018) and in individuals at high risk for depression (Olino et al., 2014), suggesting dysfunctional

TABLE 3 | Multilevel analyses of the time-lagged associations between consummatory pleasure, anticipatory pleasure and positive affect (PA) in dysphoric and non-dysphoric groups respectively and as a whole sample.

Outcome variable:	**Predictors**	**Dysphoric group**		**Non-dysphoric group**		**The whole sample**	
Consummatory pleasure (*t*)		**β(*SE*)**	***p***	**β(*SE*)**	***p***	**β(*SE*)**	***p***
Model 3							
	Anticipatory pleasure (*t*-1)	0.15 (0.04)	<0.01	0.05 (0.04)	0.22	0.08 (0.04)	0.07
Model 4							
	Anticipatory pleasure (*t*-1)	0.12 (0.03)	<0.01	0.03 (0.03)	0.30	0.05 (0.04)	0.14
	Consummatory pleasure (*t*-1)	0.06 (0.04)	0.11	0.07 (0.03)	0.03	0.08 (0.03)	<0.01
Model 5							
	Anticipatory pleasure (*t*-1)	0.08 (0.02)	<0.01	0.03 (0.02)	0.09	0.04 (0.02)	0.02
	PA (*t*)	1.83 (0.15)	<0.01	1.65 (0.13)	<0.01	1.81 (0.10)	<0.01
Model 6							
	Anticipatory pleasure (*t*-1)	0.05 (0.02)	<0.01	0.03 (0.02)	0.10	0.03 (0.02)	0.04
	Consummatory pleasure (*t*-1)	0.04 (0.03)	0.24	0.03 (0.03)	0.23	0.04 (0.02)	0.07
	PA (*t*)	1.89 (0.14)	<0.01	1.72 (0.13)	<0.01	1.80 (0.10)	<0.01

anticipatory processing in response to laboratory stimuli. The key finding that dysphoric individuals report less pleasure when anticipating future events is also consistent with research on depressed individuals' forecasts of the intensity of their PA. In general, people are over-optimistic about their future, with evidence showing that people have a tendency to overestimate the intensity and duration of PA than that they actually experience (Wenze et al., 2012; Morewedge and Buechel, 2013). This unrealistic prediction about emotional experience, though not accurate, is beneficial in maintaining mental health. With regard to evidence for biased predictions of PA in relation to depression, more severe depressive symptoms have been shown to be associated with less optimistic bias in PA prediction on a daily and a weekly basis both in the general population (Hoerger et al., 2012; Wenze et al., 2012, 2013) and in individuals with clinical and subclinical depression (MacLeod and Salaminiou, 2001; Chentsova-Dutton and Hanley, 2010). The same pattern of reduced anticipated PA has also been found in patients with remitted MDD (Thompson et al., 2017), suggesting that reduced anticipated positive experience might represent a trait-like marker in depression.

Only recently have researchers directly investigated depressed persons' anticipatory pleasure using ESM. Greater severity of subclinical symptoms of depression in the general population are found to be predictive of reduced pleasure during anticipating positive events in daily life (Bakker et al., 2017; Starr and Hershenberg, 2017). Our findings are also consistent with Wu et al.'s (2017) study in which patients with MDD demonstrated blunted state anticipatory and consummatory pleasure in relation to daily activities. On the other hand, Wu et al. (2017) also showed that patients with MDD reported levels of trait anticipatory and consummatory pleasure that were comparable to those reported by healthy controls. Self-report measures of trait anhedonia have been criticized for assessing responses to hypothetical situations that may not be comparable to actual situations, suggesting the importance of using multiple measures of anhedonia in any given study. ESM appears to be more sensitive than other methods of measuring the hedonic function of dysphoria. Given the transdiagnostic nature of anhedonia and its importance in depression, deficits in state anticipatory and consummatory pleasure might represent a core dysfunction of hedonic processing in people with dysphoria.

Daily PA is typically measured in general terms, with only limited research on the temporal experience of pleasure in response to daily events. Our finding that dysphoric and non-dysphoric individuals did not differ in their mean level of PA is consistent with study of subclinical samples (Olino et al., 2014). Moreover, in our study, dysphoric individuals, compared to non-dysphoric individuals, reported less consummatory pleasure in the course of the day. Consistent with our findings, previous research showed that patients with MDD are less responsive to positive stimuli in a laboratory task (Bylsma et al., 2008). Research with patients suffering from schizophrenia has also demonstrated a dissociation between PA and consummatory pleasure, with intact PA function but altered hedonic experience in patients compared to healthy controls (Edwards et al., 2018). In a study designed to distinguish PA and consummatory pleasure, Heininga et al. (2017) found that individuals with anhedonia reported a lower level of both PA and consummatory pleasure compared to individuals without anhedonia. Future research should further investigate the roles of the temporal experience of pleasure and current PA in depression, as well as their distinct contributions to the pathology of depression.

With regard to the predictive relationship between anticipatory and consummatory pleasure, separate models conducted within the two groups revealed significant associations between anticipatory pleasure and consummatory pleasure in the dysphoric group but not non-dysphoric group. However, models including dysphoria status as predictor did not support the moderating effect of dysphoria on these associations. Anticipatory pleasure was a significant predictor of consummatory pleasure in the whole sample, after adjustment for current PA. Thus, dysphoric and non-dysphoric individuals both report higher levels of consummatory pleasure when they anticipated greater pleasure at the previous time point, although dysphoria is associated with lower levels of anticipatory and consummatory pleasure. This result is in line with the ESM study using end-of-day dairy reports, in which it was found that the increased anticipation for positive experience and positive events of the next day predicted greater reduction of depressed symptoms in dysphoria (Starr and Hershenberg, 2017).

Levels of anticipatory pleasure are predictors of effort-expenditure for rewards in healthy volunteers (Geaney et al., 2015), and it has been suggested that depression related anticipatory pleasure deficiency is associated with impairment in translating motivation to rewarding activities (Sherdell et al., 2012; van Roekel et al., 2016; Bakker et al., 2017). For example, Bakker et al. (2017) found that the more severe the depressive symptoms, the less likely that increases in reward anticipation are to be followed by increases in PA. Moreover, the positive relationship between reward anticipation and activity engagement in controls was also diminished in individuals with dysphoria. This suggests that dysphoric individuals were not able to translate their anticipation into goal-directed behaviors to pursue the anticipated reward, which might further prevent them from experiencing pleasure. The assumption of the mediating role of approach motivation in the translational mechanism from anticipatory pleasure to the experience of consummatory pleasure remains to be tested directly in laboratory and naturalistic settings. Although further validation is required, the predictive relationships between anticipatory and consummatory pleasure in dysphoria suggest that the dysfunctional reward anticipation represents a key component of anhedonia in relation to depression.

Together, these results suggest that the lack of anticipatory pleasure may be a dominant component of impairment that affects motivated behavior and subsequent experiential feelings in depression, and deficits in anticipatory pleasure might represent a critical therapeutic target requiring further investigation. Previous studies have provided preliminary evidence for the efficacy of interventions aimed at increasing anticipatory pleasure, schizophrenia patients reported higher levels of consummatory pleasure and more frequent engagement in daily activities at the end of training (Favrod et al., 2010; Nguyen et al., 2016). Future research could examine the extent to which benefits from interventions designed to improve depressed individuals' anticipation of pleasure could translate into downstream enjoyment of pleasurable experiences.

Limitations

Our study has several limitations. Firstly, a disproportionate number of female participants were recruited, thus our results cannot be generalized to other population. Secondly, the estimated internal consistency of anticipatory subscale of TEPS is not as strong as that of consummatory subscale in present study. Anticipatory pleasure ratings are more likely to be affected by the context and therefore show less consistency than consummatory pleasure ratings (Edwards et al., 2015). In addition, the high homogeneity of college-student participants would reduce the variability in measurements (Peterson, 2001) and may affect score reliability. Thirdly, whether there are long-lasting and additive effects of anticipatory pleasure on consummatory pleasure will need to be established by further research, given evidence that anticipatory stressor together with current stressor predicted higher levels of negative affect 2.5 h later (Scott et al., 2018). Additional limitations to this study concern methodological problems in modeling time-lagged relationships, i.e., time-interval dependency (Kuiper and Ryan, 2018). Specifically, the event at *t* might not be exactly the one predicted at *t*-1, and thus the predictive relationship between anticipatory and consummatory pleasure might not reliably assess hedonic responses to the same events. To gain a better understanding of this correspondence, further research could increase the sampling density and include a more objective measure of the context in which individuals rate their experiences (e.g., by having participants indicate whether the current activity is the one that at the previous assessment they expected to be engaged in).

CONCLUSION

This study makes an important contribution to the literature of anhedonia in depression by investigating the momentary level of anticipatory and consummatory pleasure during daily life activities in dysphoric and non-dysphoric individuals. The results showed that dysphoric individuals were characterized with less state anticipatory and consummatory pleasure compared with non-dysphoric individuals, irrespective of the level of daily PA. Moreover, a significant predictive relationship was found between anticipatory pleasure and consummatory pleasure in the whole sample. Our findings build on previous research highlighting hedonic deficits in depression, showing that measures of state rather than trait anticipatory and consummatory pleasure provide better estimates for hedonic processing function in dysphoria. These findings contribute to the ecological validation of the two dimension construct of anhedonia and provide specific targets that can be used to refine existing therapeutic interventions.

DATA AVAILABILITY

The datasets generated for this study are available on request to the corresponding author.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Ethics Committee of the Central China Normal University. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

XL generated the idea, designed and supervised the study, and wrote the first draft of the manuscript. Y-TZ and Z-JH helped with data collection, data analysis, and manuscript writing. X-LC and F-HY helped with data collection and data analysis. X-JS commented significantly to the draft of the manuscript. All authors contributed to and have approved the final text.

FUNDING

This study was supported by a grant from National Natural Science Foundation of China (31700957), MOE (Ministry of Education in China) Project of Humanities and Social Sciences (17YJC190014), self-determined research funds of CCNU from the colleges "basic research and operation of MOE" (CCNU19TD018, CCNU16A05052).

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2019.02124/full#supplementary-material

REFERENCES

Admon, R., and Pizzagalli, D. A. (2015). Dysfunctional reward processing in depression. *Curr. Opin. Psychol.* 4, 114–118. doi: 10.1016/j.copsyc.2014.12.011

Arrondo, G., Segarra, N., Metastasio, A., Ziauddeen, H., Spencer, J., Reinders, N. R., et al. (2015). Reduction in ventral striatal activity when anticipating a reward in depression and schizophrenia: a replicated cross-diagnostic finding. *Front. Psychol.* 6:1280. doi: 10.3389/fpsyg.2015.01280

Bakker, J. M., Goossens, L., Lange, I., Michielse, S., Schruers, K., Lieverse, R., et al. (2017). Real-life validation of reduced reward processing in emerging adults with depressive symptoms. *J. Abnorm. Psychol.* 126, 713–725. doi: 10.1037/abn0000294

Beck, A. T., Steer, R. A., Ball, R., and Ranieri, W. F. (1996). Comparison of beck depression inventories-IA and-II in psychiatric outpatients. *J. Pers. Assess.* 67, 588–597. doi: 10.1207/s15327752jpa6703_13

Bos, F. M., Blaauw, F. J., Snippe, E., van der Krieke, L., de Jonge, P., and Wichers, M. (2018). Exploring the emotional dynamics of subclinically depressed individuals with and without anhedonia: an experience sampling study. *J. Affect. Disord.* 228, 186–193. doi: 10.1016/j.jad.2017.12.017

Bress, J. N., Smith, E., Foti, D., Klein, D. N., and Hajcak, G. (2012). Neural response to reward and depressive symptoms in late childhood to early adolescence. *Biol. Psychol.* 89, 156–162. doi: 10.1016/j.biopsycho.2011.10.004

Bylsma, L. M., Morris, B. H., and Rottenberg, J. (2008). A meta-analysis of emotional reactivity in major depressive disorder. *Clin. Psychol. Rev.* 28, 676–691. doi: 10.1016/j.cpr.2007.10.001

Bylsma, L. M., Taylor-Clift, A., and Rottenberg, J. (2011). Emotional reactivity to daily events in major and minor depression. *J. Abnorm. Psychol.* 120, 155–167. doi: 10.1037/a0021662

Chan, R. C., Shi, Y. F., Lai, M. K., Wang, Y. N., Wang, Y., and Kring, A. M. (2012). The temporal experience of pleasure scale (TEPS): exploration and confirmation of factor structure in a healthy Chinese sample. *PLoS One* 7:e35352. doi: 10.1371/journal.pone.0035352

Chentsova-Dutton, Y., and Hanley, K. (2010). The effects of anhedonia and depression on hedonic responses. *Psychiatry Res.* 179, 176–180. doi: 10.1016/j.psychres.2009.06.013

Csikszentmihalyi, M., and Larson, R. (1987). Validity and reliability of the experience-sampling method. *J. Nerv. Ment. Dis.* 175, 526–536. doi: 10.1097/00005053-198709000-00004

Edwards, C. J., Cella, M., Emsley, R., Tarrier, N., and Wykes, T. H. M. (2018). Exploring the relationship between the anticipation and experience of pleasure in people with schizophrenia: an experience sampling study. *Schizophr Res.* 202, 72–79. doi: 10.1016/j.schres.2018.06.040

Edwards, C. J., Cella, M., Tarrier, N., and Wykes, T. (2015). Investigating the empirical support for therapeutic targets proposed by the temporal experience of pleasure model in schizophrenia: a systematic review. *Schizophr. Res.* 168, 120–144. doi: 10.1016/j.schres.2015.08.013

Favrod, J., Giuliani, F., Ernst, F., and Bonsack, C. (2010). Anticipatory pleasure skills training: a new intervention to reduce anhedonia in schizophrenia. *Perspect. Psychiatr. Care* 46, 171–181. doi: 10.1111/j.1744-6163.2010.00255

Finch, W. H., and Bolin, J. E. (2017). "An introduction to multilevel data structure," in *Multilevel modeling using Mplus*, ed. K. J. Grimm (Boca Raton, FL: CRC Press, Taylor and Francis Group), 38–39.

Foti, D., Kotov, R., Klein, D. N., and Hajcak, G. (2011). Abnormal neural sensitivity to monetary gains versus losses among adolescents at risk for depression. *J. Abnorm. Child Psychol.* 39, 913–924. doi: 10.1007/s10802-011-9503-9

Gard, D. E., Gard, M. G., Kring, A. M., and John, O. P. (2006). Anticipatory and consummatory components of the experience of pleasure: a scale development study. *J. Res. Pers.* 40, 1086–1102. doi: 10.1016/j.jrp.2005.11.001

Gard, D. E., Kring, A. M., Gard, M. G., Horan, W. P., and Green, M. F. (2007). Anhedonia in schizophrenia: distinctions between anticipatory and consummatory pleasure. *Schizophr. Res.* 93, 253–260. doi: 10.1016/j.schres.2007.03.008

Gard, D. E., Sanchez, A. H., Cooper, K., Fisher, M., Garrett, C., and Vinogradov, S. (2014). Do people with schizophrenia have difficulty anticipating pleasure, engaging in effortful behavior, or both? *J. Abnorm. Psychol.* 123, 771–782. doi: 10.1037/abn0000005

Geaney, J. T., Treadway, M. T., and Smillie, L. D. (2015). Trait anticipatory pleasure predicts effort expenditure for reward. *PLoS One* 10:e0131357. doi: 10.1371/journal.pone.0131357

Gotlib, I. H., Lewinsohn, P. M., and Seeley, J. R. (1995). Symptoms versus a diagnosis of depression: differences in psychosocial functioning. *J. Consult. Clin. Psychol.* 63, 90–100. doi: 10.1037/0022-006x.63.1.90

Heininga, V. E., Dejonckheere, E., Houben, M., Obbels, J., Sienaert, P., Leroy, B., et al. (2019). The dynamical signature of anhedonia in major depressive disorder: positive emotion dynamics, reactivity, and recovery. *BMC Psychiatry* 19:59. doi: 10.1186/s12888-018-1983-5

Heininga, V. E., Van Roekel, E., Ahles, J. J., Oldehinkel, A. J., and Mezulis, A. H. (2017). Positive affective functioning in anhedonic individuals' daily life. *J. Affect. Disord.* 218, 437–445. doi: 10.1016/j.jad.2017.04.029

Hoerger, M., Quirk, S. W., Chapman, B. P., and Duberstein, P. R. (2012). Affective forecasting and self-rated symptoms of depression, anxiety, and hypomania: evidence for a dysphoric forecasting bias. *Cogn. Emot.* 26, 1098–1106. doi: 10.1080/02699931.2011.631985

Insel, T., Cuthbert, B., Garvey, M., Heinssen, R., Pine, D. S., Quinn, K., et al. (2010). Research domain criteria (RDoC): toward a new classification framework for research on mental disorders. *Am. J. Psychiatry* 167, 748–751. doi: 10.1176/appi.ajp.2010.09091379

Keren, H., O'Callaghan, G., Vidal-Ribas, P., Buzzell, G. A., Brotman, M. A., Leibenluft, E., et al. (2018). Reward processing in depression: a conceptual and meta-analytic review across fMRI and EEG studies. *Am. J. Psychiatry* 175, 1111–1120. doi: 10.1176/appi.ajp.2018.17101124

Kessler, R. C., Berglund, P., Demler, O., Jin, R., Koretz, D., Merikangas, K. R., et al. (2003). The epidemiology of major depressive disorder: results from the National Comorbidity Survey Replication (NCS-R). *JAMA* 289, 3095–3105. doi: 10.1001/jama.289.23.3095

Kring, A. M., and Caponigro, J. M. (2010). Emotion in schizophrenia: where feeling meets thinking. *Curr. Dir. Psychol. Sci.* 19, 255–259. doi: 10.1177/0963721410377599

Kuiper, R. M., and Ryan, O. (2018). Drawing conclusions from cross-lagged relationships: re-considering the role of the time-interval. *Struct. Equ. Modeling* 25, 809–823. doi: 10.1080/10705511.2018.1431046

Kuppens, P., Allen, N. B., and Sheeber, L. B. (2010). Emotional inertia and psychological maladjustment. *Psychol. Sci.* 21, 984–991. doi: 10.1177/0956797610372634

Li, Z., Lui, S. S. Y., Geng, F., Li, Y., Li, W.-X., Wang, C.-Y., et al. (2015). Experiential pleasure deficits in different stages of schizophrenia. *Schizophr. Res.* 166, 98–103. doi: 10.1016/j.schres.2015.05.041

Lissnyder, E. D., and Koster, E. H. W. (2010). The association between depressive symptoms and executive control impairments in response to emotional and non-emotional information. *Cogn. Emot.* 24, 264–280. doi: 10.1080/02699930903378354

Liu, W. H., Wang, L. Z., Zhao, S. H., Ning, Y. P., and Chan, R. C. (2012). Anhedonia and emotional word memory in patients with depression. *Psychiatry Res.* 200, 361–367. doi: 10.1016/j.psychres.2012.07.025

MacLeod, A. K., and Salaminiou, E. (2001). Reduced positive future-thinking in depression: cognitive and affective factors. *Cogn. Emot.* 15, 99–107. doi: 10.1080/02699930125776

Marchetti, I., Everaert, J., Dainer-Best, J., Loeys, T., Beevers, C. G., and Koster, E. H. W. (2018). Specificity and overlap of attention and memory biases in depression. *J. Affect. Disord.* 225, 404–412. doi: 10.1016/j.jad.2017.08.037

McFarland, B. R., and Klein, D. N. (2009). Emotional reactivity in depression: diminished responsiveness to anticipated reward but not to anticipated punishment or to nonreward or avoidance. *Depress. Anxiety* 26, 117–122. doi: 10.1002/da.20513

McMakin, D. L., Olino, T. M., Porta, G., Dietz, L. J., Emslie, G., Clarke, G., et al. (2012). Anhedonia predicts poorer recovery among youth with selective serotonin reuptake inhibitor treatment–resistant depression. *J. Am. Acad. Child Adolesc. Psychiatry* 51, 404–411. doi: 10.1016/j.jaac.2012.01.011

Morewedge, C. K., and Buechel, E. C. (2013). Motivated underpinnings of the impact bias in affective forecasts. *Emotion* 13, 1023–1029. doi: 10.1037/a0033797

Nezlek, J. B. (2012). "Multilevel modeling of diary-style data," in *Handbook Of Research Methods For Studying Daily Life*, eds M. R. Mehl, and T. S. Conner (New York, NY: Guilford Press), 357–383.

Nguyen, A., Frobert, L., McCluskey, I., Golay, P., Bonsack, C., and Favrod, J. (2016). Development of the positive emotions program for schizophrenia: an intervention to improve pleasure and motivation in schizophrenia. *Front. Psychiatry* 7:13. doi: 10.3389/fpsyt.2016.00013

Olino, T. M., McMakin, D. L., Morgan, J. K., Silk, J. S., Birmaher, B., Axelson, D. A., et al. (2014). Reduced reward anticipation in youth at high-risk for unipolar depression: a preliminary study. *Dev. Cogn. Neurosci.* 8, 55–64. doi: 10.1016/j.dcn.2013.11.005

Olsen, E. K., Bjorkquist, O. A., Bodapati, A. S., Shankman, S. A., and Herbener, E. S. (2015). Associations between trait anhedonia and emotional memory deficits in females with schizophrenia versus major depression. *Psychiatry Res* 230, 323–330. doi: 10.1016/j.psychres.2015.09.012

Owens, M., Koster, E. H., and Derakshan, N. (2012). Impaired filtering of irrelevant information in dysphoria: an ERP study. *Soc. Cogn. Affect. Neurosci.* 7, 752–763. doi: 10.1093/scan/nsr050

Peterson, R. A. (2001). On the use of college students in social science research: insights from a second- order meta-analysis. *J. Consum. Res.* 28, 450–461. doi: 10.1086/323732

Quigley, L., and Dobson, K. S. (2014). An examination of trait, spontaneous and instructed emotion regulation in dysphoria. *Cogn. Emot.* 28, 622–635. doi: 10.1080/02699931.2013.848786

Saxena, A., Luking, K. R., Barch, D. M., and Pagliaccio, D. (2017). Individual differences in hedonic capacity, depressed mood, and affective states predict emotional reactivity. *Motiv. Emotion* 41, 1–11. doi: 10.1007/s11031-017-9610-1

Schacter, D. L., Addis, D. R., and Buckner, R. L. (2008). Episodic simulation of future events. *Ann. N. Y. Acad. Sci.* 1124, 39–60. doi: 10.1196/annals.1440.001

Scott, S. B., Kim, J., Smyth, J. M., Almeida, D. M., and Sliwinski, M. J. (2018). Additive effects of forecasted and reported stressors on negative affect. *J. Gerontol. B* 74, 29–37. doi: 10.1093/geronb/gby068

Shean, G., and Baldwin, G. (2008). Sensitivity and specificity of depression questionnaires in a college-age sample. *J. Genet. Psychol.* 169, 281–292. doi: 10.3200/gntp.169.3.281-292

Sherdell, L., Waugh, C. E., and Gotlib, I. H. (2012). Anticipatory pleasure predicts motivation for reward in major depression. *J. Abnorm. Psychol.* 121, 51–60. doi: 10.1037/a0024945

Shiffman, S., Stone, A. A., and Hufford, M. R. (2008). Ecological momentary assessment. *Annu. Rev. Clin. Psychol.* 4, 1–32. doi: 10.1146/annurev.clinpsy.3.022806.091415

Snaith, R. P., Hamilton, M., Morley, S., Humayan, A., Hargreaves, D., and Trigwell, P. (1995). A scale for the assessment of hedonic tone the Snaith-Hamilton Pleasure Scale. *Br. J. Psychiatry* 167, 99–103. doi: 10.1192/bjp.167.1.99

Starr, L. R., and Hershenberg, R. (2017). Depressive symptoms and the anticipation and experience of uplifting events in everyday life. *J. Clin. Psychol.* 73, 1442–1461. doi: 10.1002/jclp.22447

Thompson, R. J., Mata, J., Jaeggi, S. M., Buschkuehl, M., Jonides, J., and Gotlib, I. H. (2012). The everyday emotional experience of adults with major depressive disorder: examining emotional instability, inertia, and reactivity. *J. Abnorm. Psychol.* 121, 819–829. doi: 10.1037/a0027978

Thompson, R. J., Spectre, A., Insel, S. P., Mennin, D. S., Gotlib, I. H., and Gruber, J. (2017). Positive and negative affective forecasting in remitted individuals with bipolar I disorder, and major depressive disorder, and healthy controls. *Cog. Ther. Res.* 41, 673–685. doi: 10.1007/s10608-017-9840-2

Thomsen, K. R., Whybrow, P. C., and Kringelbach, M. L. (2015). Reconceptualizing anhedonia: novel perspectives on balancing the pleasure networks in the human brain. *Front. Behav. Neurosci.* 9:49. doi: 10.3389/fnbeh.2015.00049

Treadway, M. T., and Zald, D. H. (2011). Reconsidering anhedonia in depression: lessons from translational neuroscience. *Neurosci. Biobehav. Rev.* 35, 537–555. doi: 10.1016/j.neubiorev.2010.06.006

van Roekel, E., Bennik, E. C., Bastiaansen, J. A., Verhagen, M., Ormel, J., Engels, R. C., et al. (2016). Depressive symptoms and the experience of pleasure in daily life: an exploration of associations in early and late adolescence. *J. Abnorm. Child Psychol.* 44, 999–1009. doi: 10.1007/s10802-015-0090-z

Watson, D., Clark, L. A., and Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: the PANAS scales. *J. Pers. Soc. Psychol.* 54, 1063–1070. doi: 10.1037//0022-3514.54.6.1063

Wenze, S. J., Gunthert, K. C., Ahrens, A. H., and Taylor Bos, T. C. (2013). Biases in short-term mood prediction in individuals with depression and anxiety symptoms. *Individ. Differ. Res.* 11, 91–101. doi: 10.1177/0146167212447242

Wenze, S. J., Gunthert, K. C., and German, R. E. (2012). Biases in affective forecasting and recall in individuals with depression and anxiety symptoms. *Pers. Soc. Psychol. Bull.* 38, 895–906. doi: 10.1177/0146167212447242

Wilcox, H. C., and Anthony, J. C. (2004). Child and adolescent clinical features as forerunners of adult-onset major depressive disorder: retrospective evidence from an epidemiological sample. *J. Affect. Disord.* 82, 9–20. doi: 10.1016/j.jad.2003.10.007

Wu, H., Mata, J., Furman, D. J., Whitmer, A. J., Gotlib, I. H., and Thompson, R. J. (2017). Anticipatory and consummatory pleasure and displeasure in major depressive disorder: an experience sampling study. *J. Abnorm. Psychol.* 126, 149–159. doi: 10.1037/abn0000244

Yang, X. H., Huang, J., Zhu, C. Y., Wang, Y. F., Cheung, E. F., Chan, R. C., et al. (2014). Motivational deficits in effort-based decision making in individuals with subsyndromal depression, first-episode and remitted depression patients. *Psychiatry Res.* 220, 874–882. doi: 10.1016/j.psychres.2014.08.056

Yuan, J. W., and Kring, A. M. (2009). Dysphoria and the prediction and experience of emotion. *Cogn. Emot.* 23, 1221–1232. doi: 10.1080/02699930802416453

Conflict of Interest Statement: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Neuroscience

ORIGINAL RESEARCH
published: 25 September 2019
doi: 10.3389/fnins.2019.00988

Discriminating Fake From True Brain Injury Using Latency of Left Frontal Neural Responses During Old/New Memory Recognition

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Traumatic brain injury (TBI) is a major public health concern that affects 69 million individuals each year worldwide. Neuropsychologists report that up to 40% of individuals undergoing evaluations for TBI may be malingering neurocognitive deficits for a compensatory reward. The memory recognition test of malingering detection is effective but can be coached behaviorally. There is great need to develop a novel neural based method for discriminating fake from true brain injury. Here we test the hypothesis that decision making of faking memory deficits prolongs frontal neural responses. We applied an advanced method measuring decision latency in milliseconds for discriminating true TBI from malingerers who fake brain injury. To test this hypothesis, latencies of memory-related brain potentials were compared among true patients with moderate or severe TBI, and healthy age-matched individuals who were assigned either to be honest or faking memory deficit. Scalp signals of electroencephalography (EEG) were recorded with a 32-channel cap during an Old/New memory recognition task in three age- and education-matched groups: honest ($n = 12$), malingering ($n = 15$), and brain injured ($n = 14$) individuals. Bilateral fractional latencies of late positive ERP at frontal sites were compared among the three groups under both studied (Old) and non-studied (New) memory recognition conditions. Results show a significant difference between the fractional latencies of the late positive component during recognition of studied items in malingerers (averaged latencies = 396 ms) and the true brain injured subjects (mean = 312 ms) in the frontal sites. Only malingers showed asymmetrical frontal activity compared to the two other groups. These new findings support the hypothesis that that additional frontal processing of malingering individuals is measurably different from those of actual patients with brain injury. In contrast to our previous reported method using difference waves of amplitudes at frontal to posterior midline sites during new items recognition (Vagnini et al., 2008), there was no significant latency difference among groups during recognition of New items. The current method using delayed left frontal neural responses during studied items reached sensitivity of 80% and specificity of 79% in detecting malingers from true brain injury.

Keywords: malinger, event-related potentials, EEG, traumatic brain injury, P3, late positive component, fractional peak latency

Edited by:
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Reviewed by:
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Specialty section:
This article was submitted to Decision Neuroscience, a section of the journal Frontiers in Neuroscience

Received: *10 April 2019*
Accepted: *02 September 2019*
Published: *25 September 2019*

Citation:
Neal J, Strothkamp S, Bedingar E, Cordero P, Wagner B, Vagnini V and Jiang Y (2019) Discriminating Fake From True Brain Injury Using Latency of Left Frontal Neural Responses During Old/New Memory Recognition. Front. Neurosci. 13:988. doi: 10.3389/fnins.2019.00988

INTRODUCTION

Traumatic brain injuries (TBIs) are attributed to 30% of all injury deaths (Taylor et al., 2017) and affect up to 69 million individuals each year worldwide (Dewan et al., 2018). People affected by TBI can suffer from the deficits of their injury for the rest of their life, potentially causing impaired memory, sensation, thinking, movement, and mood swings (Gerberding and Binder, 2003). As severe a health concern as TBI is, it is estimated by neuropsychologists that up to 40% of individuals undergoing evaluations following TBI may be malingering deficits in order to gain a compensatory reward (Mittenberg et al., 2002). Often, those who malinger, or exaggerate symptoms of TBI can be identified by intentional poor performance on cognition tests. Studies have found that, in test seeking compensation, those with mild TBI often exhibited poorer effort and worse cognitive performance than those with moderate or severe TBI (Green et al., 2001). Uncertainty in the legitimacy of the deficits of many patients affected by TBI points to a need for development of a test to screen TBI individuals to validate their deficits, while identifying malingerers.

In recent years, many studies have attempted to find effective methods to distinguish malingering behavior. Sollman and Berry (2011) conducted a large meta-analysis of detection of inadequate effort in neurophysiological testing, which included a group of 21 studies testing memory malingering. Another study has indicated the possibility that those who malinger memory deficits can be identified by the measurable physiological differences of pupil dilatation (Heaver and Hutton, 2011). Research has pointed to identification of malingerers through results of individuals undergoing new and unique testing methods based on subject performance or data processing (McBride et al., 2011; Liu et al., 2016). A classic study examined the measurement of response latency to identify malingerers when undergoing the Portland Digit Recognition Test. Using response latency, researchers were able to successfully classify 74% of malingerers (Rose et al., 1995). The success of this study implicates mental processing time and neural latencies in detection of malingerers. The methodology of using event-related potential (ERP) data to clinically differentiate malingers from those with TBI is fairly rare. If an effective method to distinguish malingering behavior from those with TBI is found, healthcare professionals will be better prepared to treat patients with the appropriate level of care. The Test of Memory Malingering (TOMM) for malingering detection is effective (Tombaugh, 1996; Kanser et al., 2019), but can be coached behaviorally. Finding new methods of identifying malingerers is a significant area of research that holds promise for the healthcare community.

Using combined methods of ERP and reaction time (RT), Vagnini et al. (2008) developed neural and behavioral methods to identify malingerers from TBI patients. The electrophysiological activity was collected using an electroencephalography (EEG) cap during. The TOMM task is a computerized method to test a subject's memory of images shown to them. Stimulus pictures were shown on a computer screen about 65 cm from the subject. The images themselves were 8 by 10 cm on a white background with a black border. The TOMM task is able to distinguish those who feign memory impairment from those with legitimate memory impairment. If a subject's score on the TOMM task is low, it suggests an exaggeration of memory impairment symptoms (Tombaugh, 1996).

Event-related potential data are averaged EEG signals that are useful for memory task analysis because the memory recognition events were time-locked to studied (Old) and New items (Finnigan, 2002). Mean ERP amplitudes for malingerers appeared to be reduced compared to those of honest or TBI subjects. Research has documented the abnormalities of ERP data within EEG signals of those with TBI. Certain character of ERP markers is linked to TBI that impact upon many cognitive functions, including processing speed, sustained attention, performance monitoring, inhibitory control, and cognitive flexibility (Dockree and Robertson, 2011). A significant component to this particular event within the EEG signal is the P3 component. The P3 component correlates to decision making and cognition when presented with a stimulus (Patel et al., 2005). The P3a component has been found to have potential to differentiate between those with TBI and those who malinger. Motivations or overt performances to feign brain injury cannot change the character of the P3a component to match that of brain injured individuals, which sets malingerers apart (Hoover et al., 2014).

In using the convenient sample, group differences were compared using advanced fractional latency methods to test a new hypothesis that decision-making of a faker needs additional frontal processing (Tombaugh, 1997). Vagnini et al. (2008) paper utilized complicated analysis of amplitudes of frontal to posterior midline electrodes, while this study focused on latency analysis of lateralized frontal electrodes not previously examined. In comparing the latencies of each subject group, significant differences in neural processing speed can be identified and attributed to the intention to malinger deficits. In contrast to combining RTs and amplitudes of multiple midline electrodes of differences waveforms, latency specific results reveal delayed decision of MNCD could indicate significant markers to identify malingering individuals.

Here we further developed a method measuring latency of neural responses in milliseconds for discriminating true TBI from malingerers who fake brain injury. We test the hypothesis that decision-making of faking memory deficits at each visual item prolongs neural responses during memory recognition.

MATERIALS AND METHODS

Participants

The behavioral and EEG data were collected from 47 age- and sex-matched individuals, which were approved by the medical IRB in the University of Kentucky. The control group was healthy, honest participants (HON) with no history of brain injury instructed to perform the task honestly to the best of their ability (mean age = 36.2; $n = 16$). The second group (MAL) was healthy individuals with no history of brain injury instructed to malinger deficits of TBI while undergoing the task (mean age = 32.7; $n = 16$). The final group consisted of patients with reported TBI instructed to perform the task honestly to the best of their ability (mean age = 40.5; n = 15) (Vagnini et al., 2008). Two participants from the TBI, one from the malingering, and four from the honest group were excluded due to excessive artifacts of EEG signals. Frontal, lateralized electrodes have more muscle artifacts compared to those at the midline electrodes. The TBI individuals ranged from moderate to severe TBI. Medical records indicate that the TBI group had a mean emergency room Glasgow Coma Scale score of 8.7 (SD = 2.9), a mean duration of loss of consciousness of 7.2 days (SD = 12.0), were an average of 13 years post-injury (SD = 7.2), and the majority (73%) were injured in moving vehicle accidents. CT and MRI scans indicated brain injury in varied locations from the brain stem, frontal, temporal, occipital, and parietal in both the left and right hemisphere (Vagnini et al., 2008).

Procedure

The study employed a 32-electrode EEG cap on subjects while undergoing the Old/New Memory Task. Participants' performances (accuracy and reaction times) were recorded along with EEG scalp signals. Data were recorded using Neuroscan 4.5 and analyzed using EP Toolkit 2.0. This was done by comparing the results from detecting MNCD to the results of the established testing method (TOMM-C) (Tombaugh, 1996, 1997; Vagnini et al., 2008; Kanser et al., 2019).

Task

The Old/New task began with a study phase of 100 New drawings. Stimulus pictures were displayed on a computer screen, which were presented for 5 s each during the study phase, and participants were instructed to memorize each picture. After a short break, all 100 pictures were studied again for a second time. After studying the pictures, the participants entered the test phase. Participants viewed 140 pictures, presented one time (70 old and 70 foils not yet presented to the participant). For each picture, the participant decided whether the drawing was "New" or "Old" and clicked a corresponding key on the keyboard (**Figure 1**).

Data Analysis

Standard EEG preprocessing were performed (e.g., removing artifacts). They have been reported in detail previously (Vagnini et al., 2008). Here, we picked the largest ERP components, P3 or late positive component for latency analysis. The research done by the ABC lab has focused on the P3 component of the ERP data collected. By focusing on the P3 component of ERP data rather than the mean ERP data alone, more specific results relating to the decision of MNCD could indicate significant markers to identify malingering individuals (Levada et al., 2016).

The latency analysis utilized MATLAB in combination with the extension EEGLAB and ERPLAB (Lopez-Calderon and Luck, 2014). Bilateral anterior and posterior sites were selected for analysis of fractional peak latency, which measures latency by finding the peak amplitude and then working backward in the waveform until 50% of that peak voltage is reached. Compared to simple peak latency, this is a better method that is optimal for finding onset latency and allows for most accurate results. The peak measures were tested for between group differences with a one-way ANOVA with a significance at the 0.05 level.

To further examine the implications of peak latency differences between groups, amplitudes from −200 to 600 ms at potentially significant electrodes were also examined. Significant electrodes areas were visualized from the development of scalp topographic maps of subjects over the same time frame. The topographic maps were created based on grand averaged data of all subjects within a testing group, done with MATLAB.

RESULTS

To test the hypothesis of frontal manipulation among healthy individuals faking brain injury, we examined latencies of P3 in several bilateral frontal electrodes (i.e., FP1, FP2, F3, and F4; See **Figure 2**). Significant group differences were found with the Old (studied) memory recognition at these frontal electrodes. In using fractional peak latency analysis on these electrodes, the fractional peak latency for each subject group was compared to the grand averaged voltage data of brain activity over the −200 to 600 ms time frame for each group. This analysis allowed for visualization of the differences in peak latency between subject groups during Old (studied) memory recognition (**Figure 3**). As well as visualization, the data was tested for significance through a one-way ANOVA with a significance at the 0.05 level. The statistical analysis yielded results of significant differences in peak latency between MAL and TBI groups at the FP1, F3, and F4 electrodes for the Old condition only (**Table 1**). The largest latency differences between true TBI and malingerers are at the F3 site. The malingerers of memory deficits are on average 88 ms longer in the left frontal site. Latencies were also examined at occipital electrodes, but no significant group differences were found.

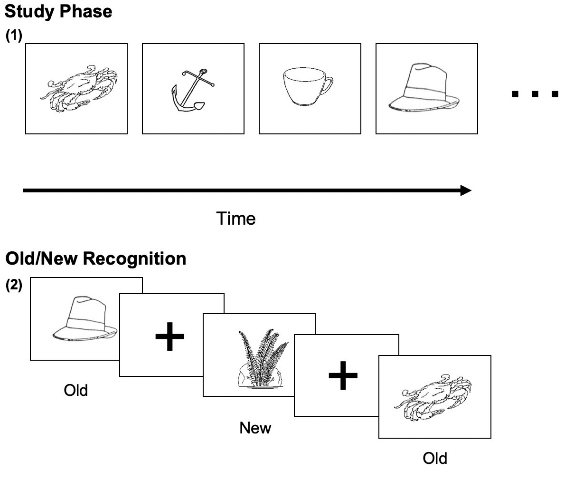

FIGURE 1 | Sample visual stimuli of the Old/New Task. **(1)** The studied (Old) visual object image (5 s each); **(2)** Old/New decision on studied and new (non-studied) images.

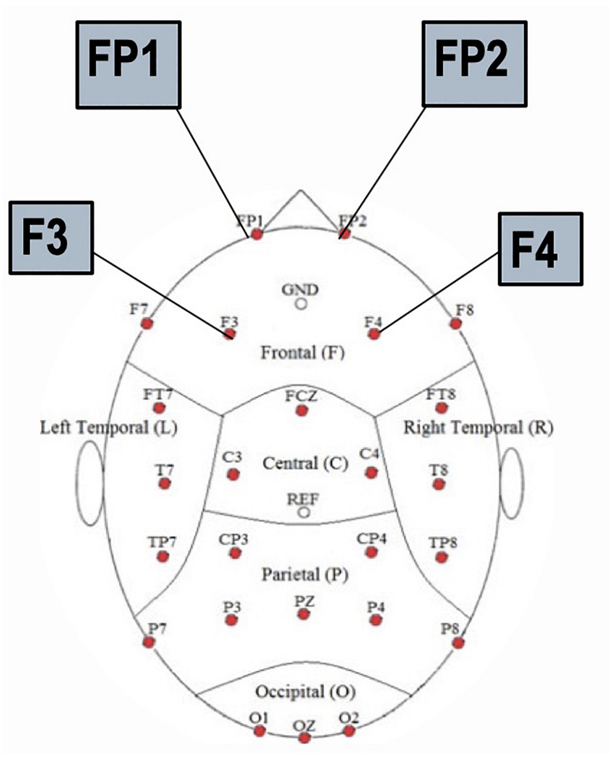

FIGURE 2 | Locations of the frontal electrodes FP1, FP2, F3, and F4 on the 32 channel EEG cap.

Topographic maps created with the resultant data indicated the brain regions with the highest average amplitude of activity during testing for subject groups, identified by dark red regions on the **Figure 4**. The information gathered from the topographic maps indicated that significant electrodes for analysis were located in the frontal and visual cortices as shown.

The significance of the latency differences can also be visualized through scatter plot (**Figure 5**). Each group is represented by color (red = malingering, green = brain injured) with each point representing an individual subject. Honest subjects were not visualized in the figure because the aim is to differentiate malingerers from brain injured individuals. The solid black line at 361 ms represents the threshold of significant group differences in latency. The red points to the right of the line represent true positive values as they are delayed malingering latencies. The red marks to the left of the line represent false negative values as they are malingerers without significantly delayed latencies. The green marks to the left of the line represent the true negative values as they are traumatic brain injured individuals with no delay in latency. The green marks to the right of the line represent false positive values as they are brain injured individuals with delayed latencies. Using these values, the sensitivity or hit rate was calculated to be 80%, meaning that in using delayed latencies, 80% of malingering individuals will be positively identified. The specificity was also calculated with these values and found to be 79%.

DISCUSSION

We report new findings that the left frontal neural responses during recognition decision of studied visual stimuli are significantly delayed in malingerers compared to those in true patients with traumatic brain injured. The results indicate an averaged delay of 396 ms for malingerers compared to a 312 ms averaged delay for TBI individuals, marking an 84-ms difference in cognitive processing between the two groups. The results also indicate honest individuals using primarily bilateral frontal engagement when viewing both Old and New images. In contrast, malingering individuals engaged right frontal and left occipital regions in response to both New and Old images. Individuals with traumatic brain injuries engaged in distributed cortices: frontal, parietal, and mostly the right occipital visual cortex in response to both New and Old images. These differences in regional engagement between test groups are most evident from the scalp topographic maps and indicate notable differences in brain activity, not only between healthy and brain injured individuals, but also between individuals responding honestly to stimuli versus those malingering deficits.

TABLE 1 | The average fractional latency (ms) of bilateral frontal electrode sites.

FP1	**P3 latency (ms)**		**FP2**	**P3 latency (ms)**	
	Old	**New**		**Old**	**New**
HON	327.2 ± 56.9	344.0 ± 49.6	HON	332.8 ± 56.8	344.7 ± 48.5
MAL	375.7 ± 38.6*	389.7 ± 28.7	MAL	366.6 ± 44.9	381.3 ± 34.5
TBI	307.8 ± 73.5*	328.4 ± 71.9	TBI	337.3 ± 79.2	323.2 ± 63.3
F3*	**P3 latency (ms)**		**F4**	**P3 latency (ms)**	
	Old	**New**		**Old**	**New**
HON	326.3 ± 57.6	369.7 ± 59.5	HON	338.0 ± 55.6	372.7 ± 56.1
MAL	397.5 ± 43.6*	389.2 ± 35.1	MAL	390.1 ± 48.0*	375.9 ± 44.1
TBI	309.4 ± 55.1*	313.7 ± 77.4	TBI	310.9 ± 69.2*	342.7 ± 74.3

*$p < 0.05$.

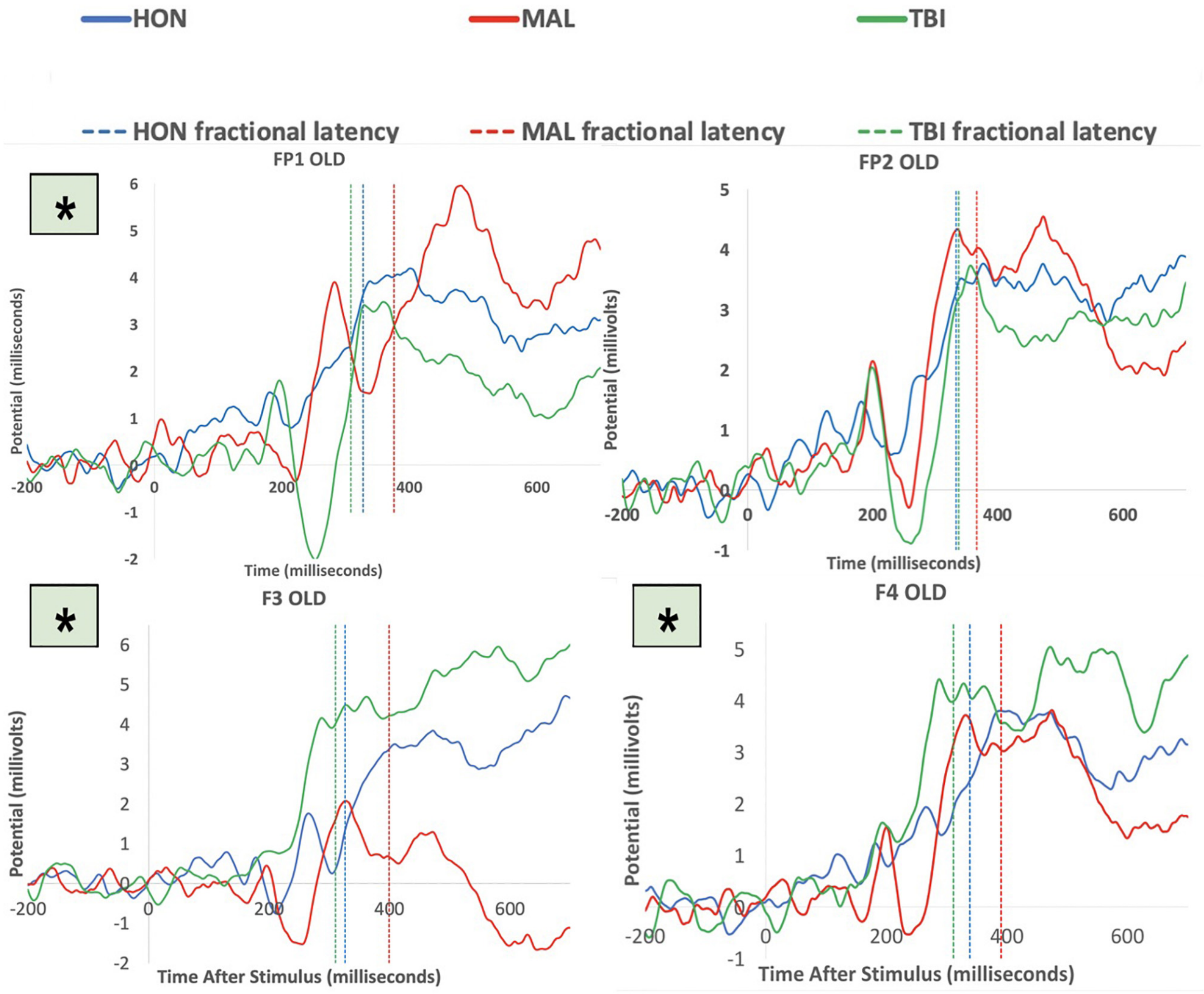

FIGURE 3 | Group averaged responses during Old items at the electrodes FP1, FP2, F3, and F4. Solid lines represent grand average of ERP responses of honest subjects (blue), malingering subjects (red), and TBI subjects (green) at each electrode site. Dashed lines represent the averaged fractional peak latencies of each group with the same corresponding colors. Asterisks indicate significant results at the electrode. Note that all significant group differences between MAL and true TBI were during memory recognition of studied items.

The decision factors about ERP old/new effects was found to be associated with the late positive components (LPC) responses which had a left > right, centro-parietal scalp topography (Finnigan, 2002). Thus our analysis focused on lateralized electrodes. We found that only maligning group had asymmetrical frontal activity during their decision of whether to lie or not about an old-item. This frontal engagement might be the involvement of the working memory required to plan and exhibit TBI-like memory failure. Interestingly, during a modified delayed match-to-sample task, left-frontal memory related potentials during the working memory task discriminated healthy older adults and those with mild cognitive impairment patients. The LPC in the right frontal ERPs were statistically identical between normal older adults and those with early Alzheimers' disease (Li et al., 2017). Fletcher and Henson (2001) determined there are two types of working memory tasks: "delayed matching tasks" and "self-ordered tasks." The faking/fringing TBI process may require a malinger to determine if a probe stimulus matches a stimulus held in their memory similar to Old/New task in the experiment and then a self-ordered task to be honest or not for this item (Fletcher and Henson, 2001). Both the honest and TBI individuals performed to the best of their ability and merely answered whether they had seen the image previously. In contrast, the malingerers' responses required different brain engagement because of their conscious effort exhibit TBI-like behavior, which is more similar to the "self-ordered tasks." According to Petrides, individuals performing "delayed matching tasks" show engagement in the ventrolateral frontal cortex, while those performing "self-ordered tasks" show engagement in the dorsolateral frontal cortex (Petrides, 1995). These differing areas of engagement show further distinction between the neural responses of malingerers to that of honest and TBI individuals.

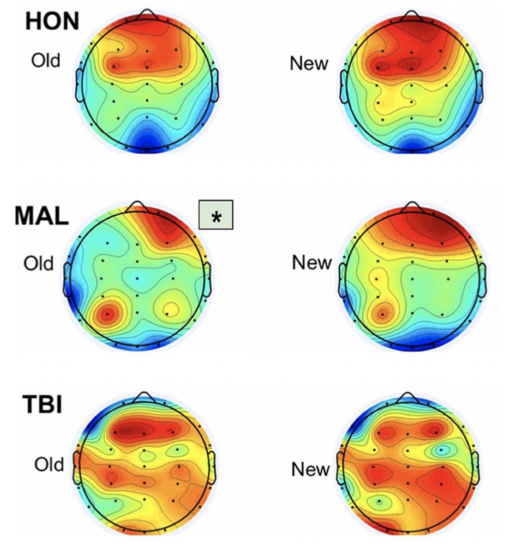

FIGURE 4 | Topographic maps from the three testing groups representing averaged activity from 250 to 400 ms. Group differences were found only during old items. Asterisk indicates significant differences from other groups.

The left occipital engagement illustrates the visual processing of the malingerers as they viewed the images presented and determined if they had seen it before (Sehatpour et al., 2008). This engagement differs from honest participants whose engagement was focused mainly frontal bilaterally implying that honest participants engaged frontal-occipital communications differently from the malingerers because they were attempting to determine the correct categorization of the image (Old/New) while malingerers were less concerned with accuracy and more so with exhibiting a TBI-like performance.

Our present findings demonstrate a simpler way to measure neural delay that is harder to fake, which may lead to better clinical identifications of true TBI individuals from those who malinger deficits. The ERP results illustrate that the Old/New Memory task can provide clinicians with distinguishable markers in brain activity to differentiate malingerers from those with legitimate TBI. Although this form of testing is not immediate and requires the subject to perform the memory task, it yields quantifiable results to accurately identify TBI individuals and allow for them to get proper treatment without concern of exaggeration or malingering.

Although the results of analysis of P3 signatures found promising results, research has found that splitting the P3 signature into two components, P3a and P3b, could yield results more tailored to specific events (Polich, 2007). The P3a component deals specifically with detection of a stimulus, an involuntary response, while the P3b response is the conscious task-relevant processing of the stimulus (Hoover et al., 2014). Our results are consistent with the P3b component. In isolating specifically, the P3a component, comparisons

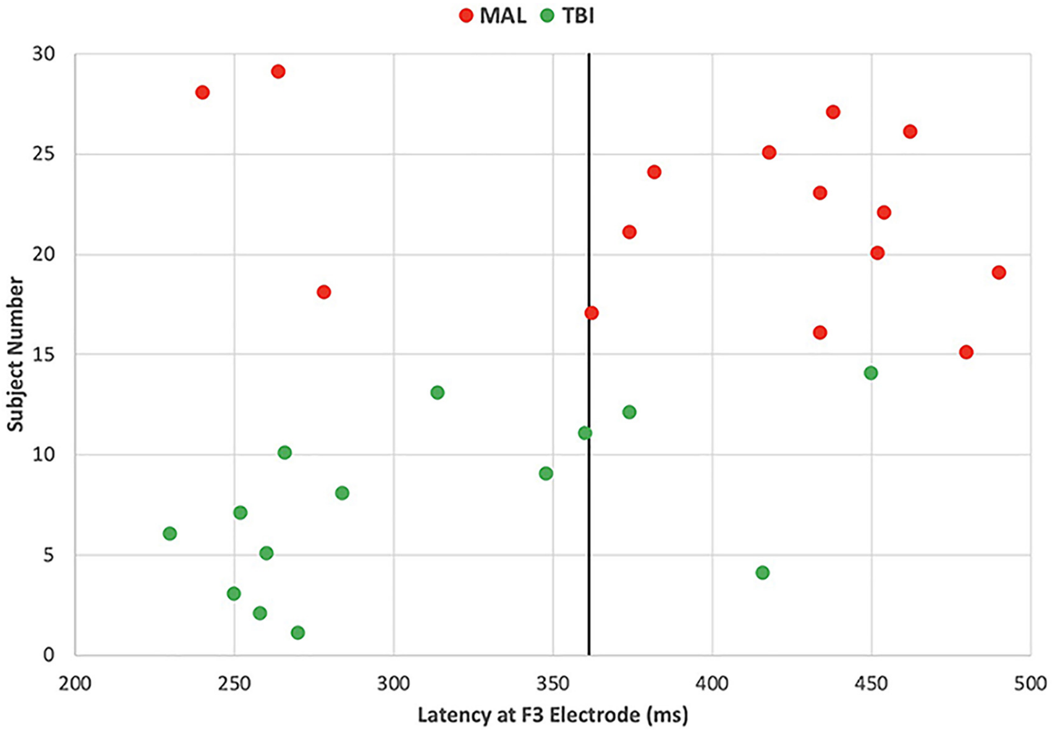

FIGURE 5 | Individual's latency at one left frontal site differentiates malingers with 80% sensitivity and 79% of specificity. Each point represents an individual subject's P3 latency at a left frontal (F3) site, color coded by subject groups with red representing malingering and green representing brain injured individuals. The solid black line represents the delayed latency threshold at 361 ms.

can be made between malingerers and TBI individuals that can identify malingerers. Individuals attempting to malinger cognitive impairment could not simulate comparable P3a deficits seen in those with legitimate TBI. Abnormalities of these components may signal other mental disorders (Hoover et al., 2014; Bachiller et al., 2015). Because P3a is an involuntary reaction, differences in this component specifically can be a promising identifier of malingerers.

The findings are promising, but there are several limitations to the research. First, cross-validations with independent samples are important for this type of application. Second, the current method is limited in differentiating a liar from a TBI patient, or from healthy honest, but it is not clinical diagnosis test in TBI patient. Also, the sample size of each group (12–15 individuals) is small and presents problems in attempts to generalize these results to a larger population without significant effect size. Additionally, the sample size is too small to examine sex differences in brain responses during decision-making.

Recent advancement of EEG recording makes EEG screening wireless and easier to use in the clinics. Technological advances have made the use of EEG testing and ERP analysis more accessible in clinical settings. These results illustrate the possibilities of the use of ERP analysis in TBI vetting for future studies. This experiment is the early stages of more promising and expansive results. New, independent sampling and data collection is needed to further validate these findings and achieve concrete predictive values for those with TBI and those who malinger.

In practice, identification of those malingering deficits of TBI can be useful for not only healthcare professionals, but also those involved in insurance and legal processing. Vallabhajosula (2015) discusses the implications of employing neuroscience in criminal law, specifically detailing malingering and its assessment. Malingering can have legal implications where people are able to lie or exaggerate symptoms to avoid criminal conviction or military service. It is difficult for legal professionals to identify malingerers without proof because they can be accused of defamation by the potential malingerer (Weiss and Van Dell, 2017). The consequences of malingering are great; for military settings, those malingering deficits of injury or disability to avoid military service are subject to court-marshal and punishment (Malingering 83 U. S. C. §. 883, 2016). The promising findings of definitive methods of identification of malingerers can have great use to identify those malingering deficits to avoid legal responsibilities. With effective testing allowing for differentiation between TBI individuals and those malingering deficits, neurological signatures identified through research can help identify dishonest individuals. These techniques can be put into practice in court proceedings to distinguish honest individuals from those providing false testimony.

The present results contribute to future studies in developing combined methods of differentiation between TBI individuals and malingerers. For instance, machine learning type of classifications applying frontal latencies, frontal-parietal amplitudes and task performance (accuracy and reaction times) will greatly improve the precision. Previous study has found that larger P3 amplitudes correlate to faster behavioral responses, but peak amplitude latencies do not differ for behavioral reaction times (Ramchurn et al., 2014). Using fractional peak latency to compare the P3 signatures to reaction times could yield promising results. This method could allow for another form identification of possible differences in behavioral markers during memory tasks that can differentiate test groups. Research could also be useful in exploring more detailed identification of TBI to differentiate those with mild TBI versus those with severe. The Glasgow Coma Scale was developed to determine the level of consciousness of a person after a TBI. On the scale, a score of 13–15 is classified as mild, 9–12 as moderate, and 8 or less as severe (Teasdale and Jennett, 1974). Categorizing the TBI participants in the study could yield more specific results based on the severity of their brain injury. Studies have found that mild TBI results in prolonged P3 latencies at central electrodes compared to healthy individuals (Nandrajog et al., 2017). In contrast, the results found in this study show that the moderate to severe TBI individuals have early onset peak P3 latencies compared to healthy individuals. Differences in peak latencies could indicate a discernable pattern in brain activity based on the severity of TBI. In using methods to better detail the extent of TBI, patients would be able to receive more appropriate and tailored care for their level of injury.

DATA AVAILABILITY

The datasets generated for this study are available on request to the corresponding author.

AUTHOR CONTRIBUTIONS

JN was responsible for writing the manuscript and performed some data analysis and interpretation. SS was involved in the data analysis of the fractional latency and interpretation as well as helped with the writing. EB contributed to the data analysis and drafting the manuscript. PC was aided with data analysis and interpretation. BW was responsible for early data analysis and interpretation. VV designed and collected the clinical and EEG data as part of her Ph.D. dissertation. YJ contributed to the study design, EEG data collection, analysis, interpretation, and writing the manuscript.

FUNDING

This work was supported in part by the grant funding from the Henry M. Jackson Foundation and the National Institute on Aging to YJ (1R56AG060608).

ACKNOWLEDGMENTS

We thank Dr. S. McIlwarth for helping discussion.

REFERENCES

Bachiller, A., Romero, S., Molina, V., Alonso, J. F., Mañanas, M. A., Poza, J., et al. (2015). Auditory P3a and P3b neural generators in schizophrenia: an adaptive sLORETA P300 localization approach. *Schizophr. Res.* 169, 318–325. doi: 10.1016/j.schres.2015.09.028

Dewan, M. C., Rattani, A., Gupta, S., Baticulon, R. E., Hung, Y. C., Punchak, M., et al. (2018). Estimating the global incidence of traumatic brain injury. *J. Neurosurg.* 1, 1–18. doi: 10.3171/2017.10.JNS17352

Dockree, P. M., and Robertson, I. H. (2011). Electrophysiological markers of cognitive deficits in traumatic brain injury: a review. *Int. J. Psychophysiol.* 82, 53–60. doi: 10.1016/j.ijpsycho.2011.01.004

Finnigan, S. (2002). ERP "old/new" effects: memory strength and decisional factor(s). *Neuropsychologia* 40, 2288–2304. doi: 10.1016/S0028-3932(02)00113-6

Fletcher, P. C., and Henson, R. N. A. (2001). Frontal lobes and human memory: insights from functional neuroimaging. *Brain* 124, 849–881. doi: 10.1093/brain/124.5.849

Gerberding, J. L., and Binder, S. (2003). *National Center for Injury Prevention and Control. Report to Congress on Mild Traumatic Brain Injury in the United States: Steps to Prevent a Serious Public Health Problem*. Available at: https://www.cdc.gov/traumaticbraininjury/pdf/mtbireport-a.pdf (accessed April 17, 2003).

Green, P., Rohling, M. L., Lees-Haley, P. R., and Allen, L. M. (2001). Effort has a greater effect on test scores than severe brain injury in compensation claimants. *Brain Inj.* 15, 1045–1060. doi: 10.1080/02699050110088254

Heaver, B., and Hutton, S. B. (2011). Keeping an eye of the truth? Pupil size changes associated with recognition memory. *Memory* 4, 398–405. doi: 10.1080/09658211.2011.575788

Hoover, S., Zottoli, T., and Grose-Fifer, J. (2014). ERP correlates of malingered executive disfunction. *Int. J. Psychophysiol.* 91, 139–146. doi: 10.1016/j.ijpsycho.2013.12.009

Kanser, R. J., Rapport, L. J., Bashem, J. R., and Hanks, R. A. (2019). Detecting malingering in traumatic brain injury: combining response time with performance validity test accuracy. *Clin. Neuropsychol.* 33, 90–107. doi: 10.1080/13854046.2018.1440006

Levada, O. V., Cherednichenko, N. V., and Gorbachev, S. V. (2016). Parameters of the P300 potential in mild neurocognitive disorders of different etiologies. *Neurophysiology* 48, 414–420. doi: 10.1007/s11062-017-9618-x

Li, J., Broster, L. S., Jicha, G. A., Munro, N. B., Schmitt, F. A., Abner, E., et al. (2017). A cognitive electrophysiological signature differentiates amnestic mild cognitive impairment from normal aging. *Alzheimer's Res. Ther.* 9:3. doi: 10.1186/s13195-016-0229-3

Liu, Z., Dong, J., Zhao, X., Chen, X., Lippa, S. M., Caroselli, J. S., et al. (2016). Assessment of feigned cognitive impairment in severe traumatic brain injury patients with the forced-choice graphics memory test. *Brain Behav.* 6:e00593. doi: 10.1002/brb3.593

Lopez-Calderon, J., and Luck, S. J. (2014). ERPLAB: an open-source toolbox for the analysis of event-related potentials. *Front. Hum. Neurosci.* 8:213. doi: 10.3389/fnhum.2014.00213

Malingering 83 U. S. C. §. 883 (2016).

McBride, J., Zhao, X., Nichols, T., Abdul-Ahad, T., Wilson, M., and Vagnini, V. (2011). "Classification of traumatic brain injury using support vector machine analysis of event-related Tsallis entropy," in *Proceedings of the 2011 Biomedical Sciences and Engineering Conference: Image Informatics and Analytics in Biomedicine* (Knoxville, TN: IEEE), 1–4.

Mittenberg, W., Patton, C., Canyock, E. M., and Condit, D. C. (2002). Base rates of malingering and symptom exaggeration. *J. Clin. Exp. Neuropsychol.* 24, 1094–1102. doi: 10.1076/jcen.24.8.1094.8379

Nandrajog, P., Idris, Z., Azlen, W. N., Liyana, A., and Abdullah, J. M. (2017). The use of event-related potential (P300) and neuropsychological testing to evaluate cognitive impairment in mild traumatic brain injury patients. *Asian J. Neurosurg.* 12, 447–453. doi: 10.4103/1793-5482.180921

Patel, Salil, H., and Azzam, P. N. (2005). Characterization of N200 and P300: selected studies of the event-related potential. *Int. J. Med. Sci.* 2, 147–154. doi: 10.7150/ijms.2.147

Petrides, M. (1995). Impairments on non-spatial self-ordered and externally ordered working memory tasks after lesions of the mid-dorsal part of the lateral frontal cortex in the monkey. *J. Neurosci.* 15, 359–375. doi: 10.1523/JNEUROSCI.15-01-00359.1995

Polich, J. (2007). Updating P300: an integrative theory of P3a and P3b. *Clin. Neurophysiol.* 118, 2128–2148. doi: 10.1016/j.clinph.2007.04.019

Ramchurn, A., de Fockert, J. W., Mason, L., Darling, S., and Bunce, D. (2014). Intraindividual reaction time variability affects P300 amplitude rather than latency. *Front. Hum. Neurosci.* 8:557. doi: 10.3389/fnhum.2014.00557

Rose, F. E., Hall, S., and Szalda-Petree, A. D. (1995). Portland digit recognition test – computerized: measuring response latency improves the detection of malingering. *Clin. Neuropsychol.* 9, 124–134. doi: 10.1080/13854049508401594

Sehatpour, P., Molholm, S., Schwartz, T. H., Mahoney, J. R., Mehta, A. D., Javitt, D. C., et al. (2008). A human intracranial study of long-range oscillatory coherence across a frontal–occipital–hippocampal brain network during visual object processing. *Proc. Natl. Acad. Sci.* 105, 4399–4404. doi: 10.1073/pnas.0708418105

Sollman, M. J., and Berry, D. T. R. (2011). Detection of inadequate effort on neuropsychological testing: a meta-analytic update and extension. *Arch. Clin. Neuropsychol.* 26, 774–789. doi: 10.1093/arclin/acr066

Taylor, C. A., Bell, J. M., Breiding, M. J., and Xu, L. (2017). Traumatic brain injury – related emergency deprartment visits, hospitalizations, and deaths – United States, 2007 and 2013. *MMWR Surveill. Summ.* 66, 1–16. doi: 10.15585/mmwr.ss6609a1

Teasdale, G., and Jennett, B. (1974). Assessment of coma and impaired consciousness. *Lancet* 1974, 81–84. doi: 10.1016/s0140-6736(74)91639-0

Tombaugh, T. N. (1996). *Test of Memory Malingering (TOMM)*. New York, NY: Multi-Health Systems, Inc.

Tombaugh, T. N. (1997). The test of memory malingering (TOMM): normative data from cognitively intact and cognitively impaired individuals. *Psychol. Assess.* 9, 260–268. doi: 10.1037//1040-3590.9.3.260

Vagnini, V., Berry, D., Clark, J., and Jiang, Y. (2008). New measures to detect malingered neurocognitive deficit: applying reaction time and event-related potentials. *J. Clin. Exp. Neuropsychol.* 30, 766–776. doi: 10.1080/13803390701754746

Vallabhajosula, B. (2015). *Murder in the Courtroom: The Cognitive Neuroscience of Violence*. New York, NY: Oxford University Press.

Weiss, K. J., and Van Dell, L. (2017). Libability for diagnosis malingering. *J. Am. Acad. Psychiatry Law* 45, 339–347.

Conflict of Interest Statement: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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ORIGINAL RESEARCH
published: 24 October 2019
doi: 10.3389/fpsyg.2019.02402

The Mediating Role of Coping Styles on Impulsivity, Behavioral Inhibition/Approach System, and Internet Addiction in Adolescents From a Gender Perspective

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Previous findings have shown that impulsivity and Behavioral Inhibition/Approach System (BIS/BAS) have substantial effects on adolescents' Internet addiction, but the mechanisms underlying these associations and gender differences in these effects have received little attention. We examined the mediating effects of coping styles from impulsivity, and BIS/BAS to Internet addiction as well as gender differences in these associations. A total of 416 Chinese adolescents were examined using a cross-sectional survey involving Young's Diagnostic Questionnaire for Internet Addiction, Barratt Impulsiveness Scale, BIS/BAS scales, and Coping Style Scale for Middle School Students. The data were analyzed using the independent sample *t*-test, chi-square test, Pearson correlation, and structure equation modeling. The results from the multiple-group (by adolescent gender) structural model analysis revealed that both impulsivity ($p < 0.001$) and BIS ($p = 0.001$) directly predicted positive Internet addiction in girls, while both impulsivity ($p = 0.011$) and BAS ($p = 0.048$) directly predicted positive Internet addiction in boys. Furthermore, emotion-focused coping mediated the relationship between impulsivity and Internet addiction ($\beta = 0.080$, 95% CI: 0.023–0.168) and the relationship between BIS and Internet addiction ($\beta = 0.064$, 95% CI: 0.013–0.153) in girls, while in boys, problem-focused coping and emotion-focused coping mediated the association between impulsivity and Internet addiction ($\beta = 0.118$, 95% CI: 0.031–0.251; $\beta = 0.065$, 95% CI: 0.010–0.160, respectively) and problem-focused coping mediated the association between BAS and Internet addiction [$\beta = -0.058$, 95% CI: (-0.142)–(-0.003)]. These findings extend our insight into the mechanisms underlying the associations among impulsivity, BIS/BAS, and Internet addiction in adolescents and suggest that gender-sensitive training approaches to decrease adolescents' Internet addiction are indispensable. These interventions should focus on the different gender predictors of adolescent Internet addiction and on the development of specific coping styles for boys and girls respectively.

Keywords: adolescents, impulsivity, behavioral inhibition/approach system, coping styles, Internet addiction, gender differences

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Specialty section:
This article was submitted to
Decision Neuroscience,
a section of the journal
Frontiers in Psychology

Received: *05 June 2019*
Accepted: *08 October 2019*
Published: *24 October 2019*

Citation:
Li Q, Dai W, Zhong Y, Wang L, Dai B and Liu X (2019) The Mediating Role of Coping Styles on Impulsivity, Behavioral Inhibition/Approach System, and Internet Addiction in Adolescents From a Gender Perspective. Front. Psychol. 10:2402. doi: 10.3389/fpsyg.2019.02402

INTRODUCTION

With the speedy development of Internet technology in recent years, people increasingly use the Internet, especially adolescents. Although the growth in Internet use facilitates adolescent life in many ways, excessive Internet use can lead to Internet addiction (Choi et al., 2009; Ko et al., 2012). Internet addiction was defined as a subset of behavioral addictions that possess the core components of addiction, such as salience, tolerance, and withdrawal (Griffiths, 2000), while Shapira et al. (2000) described Internet addiction as an impulse control disorder. In 2008, Shaw and Black (2008) further refined the conception of "Internet addiction" as "excessive or poorly controlled preoccupations, urges or behaviors regarding computer use and Internet access that lead to impairment or distress." In consideration of the variety of terminologies, the lack of consistency about the conceptualization and the diagnosis of Internet addiction, Sim et al. (2012) have suggested that the most reliable and valid criterion for conceptualizing Internet addiction is to adapt the Diagnostic and Statistical Manual of Mental Disorders, 4th Edition (DSM- IV) criteria for pathological gambling. Consistent with this notion, Young defined Internet addiction as an individual's inability to control the impulse to use their Internet use, which eventually leads to psychological, social, educational, and/or occupational problems (Young, 1998). Furthermore, she confirmed 8 symptoms of Internet addiction according to the criteria for pathological gambling in the DSM-IV: tolerance, preoccupation, withdrawal symptoms, unsuccessful attempts to decrease use, continued excessive use, compromise or loss of a significant relationship and social activities, lying about online activity, and use of the Internet to self-medicate. Meanwhile, she developed a brief eight-item Diagnostic Questionnaire for Internet Addiction (YDQ) to assess Internet addiction (Young, 1998). Although Internet addiction has not yet been classified as a disorder, neither in the DSM-V nor in the eleventh edition of the International Classification of Diseases (ICD-11), most of the items in YDQ directly corresponded to the nine diagnostic criteria for Internet Gaming Disorder in the DSM-V (American Psychiatric Association [APA], 2013). Furthermore, "chemical" addiction showed no difference with "behavioral" addiction according to DSM-V addiction criteria, and DSM-V paid more attention to personal experiences rather than drug types (American Psychiatric Association [APA], 2013). Subsequently, Internet Gaming Disorder was included as "Disorders due to addictive behaviors" rather than as an "Impulse Control Disorder" in the ICD-11 (World Health Organization [WHO], 2018).

Adolescence is a critical stage in life cycle, and can be defined as a transitional period from childhood to adulthood during which individuals experience major biological, cognitive, and socioaffective changes (Dumont and Provost, 1999). Consequently, adolescents have to cope with the most stressful life-events and the challenges caused by these changes. They face specific developmental tasks including identity construction, personal autonomy, and the redefinition of relationships with adults and peers (Borca et al., 2015). Internet addiction is highly prevalent and causes more harmful consequences among adolescents than among adults in many countries due to their active psycho-social and personality development (Morrison and Gore, 2010; Spada, 2014; Stavropoulos et al., 2017). The data from a nationally representative sample of Chinese adolescents indicated that the percentage of Internet addicts in the total sample (Internet users and non-Internet users) was 6.3% (1,523/24,013), while among Internet users, it was 11.7% (1,523/12,993) (Li et al., 2014). In addition, the prevalence of Internet addiction is much higher in Asian countries (e.g., China) than in Western countries (Li et al., 2018). Moreover, Internet addiction is significantly correlated with numerous negative consequences in adolescents, such as psychiatric disorders (e.g., depression, anxiety and obsessive-compulsive specifications), physical problems, and poor academic performance (Ko et al., 2009; Salmela-Aro et al., 2017; Przepiorka et al., 2019). More importantly, addiction and its' negative influences in adolescents could continue into adulthood (Englund et al., 2008; Stavropoulos et al., 2017). Thus, it is very important to study Internet addiction among adolescents. To promote the prevention of and early intervention for Internet addiction, it is imperative to identify risk factors and underlying mechanisms for Internet addiction in adolescents, especially among those in Asian countries.

The dual-system neurobiological model tries to explain high risk-taking behaviors in adolescents, such as substance abuse, pathological gambling, Internet gaming disorders, and so on (Casey et al., 2008). It proposes that the differential development of the reward-seeking and impulse control system in adolescents, which show heightened reward-seeking and deficient impulse control relative to children and adults, might be one of the most important factors contributing to the high incidence of adolescents' risky behaviors (Steinberg, 2010). This model goes against traditional explanations, which states that risky behaviors in adolescents are mainly due to a lag in the development of the prefrontal control system and advocates to combine the development of the subcortical reward-seeking system with that of the prefrontal control system (Rubia et al., 2000, 2006; Tamm et al., 2002; Yurgelun-Todd, 2007). In line with the dual-system model, many neurobiological models indicate that the reward system and impulse control system have equal importance in terms of accounting for adolescent's risky behaviors, including substance abuse and problematic gambling (Casey et al., 2008; Steinberg, 2008; Somerville and Casey, 2010). However, few studies have simultaneously explored the characteristics of reward processing and impulse control in the context of Internet addition among adolescents to test and extend the dual-system model for this condition.

Impulsivity, BIS/BAS and Internet Addiction

Impulsivity is defined as a predisposition that leads to the tendency to behave prematurely and without foresight in ways that are undesirably dangerous or unsuitable to the situation (Robbins et al., 2012). Impulsivity is often associated with the inhibitory control systems due to an immature frontal lobe that causes adolescents to be at particularly high risk for Internet addiction (Crews and Boettiger, 2009; Brand et al., 2014). Previous studies have revealed that the high level of Internet addiction among adults is positively associated with impulsivity (Meerkerk et al., 2010; Zhang et al., 2015), and adolescents with Internet addiction exhibit increased impulsivity and reduced inhibitory control capacity compared with controls (Cao et al., 2007; Choi J. S. et al., 2014; Choi S.-W. et al., 2014; Bargeron and Hormes, 2017). Many researchers have emphasized the key role of impulsivity in Internet addiction and have argued that impulsivity is an important risk factor for developing Internet addiction and a marker of susceptibility to Internet addiction (Lee et al., 2012; Wu et al., 2013; Li et al., 2016).

Gray's neuropsychological reinforcement sensitivity theory states that behavior originates from activity in at least two basic dimensions of motivation, which are independent and based on biological systems (Gray, 1994; Bijttebier et al., 2009). These dimensions reveal the function of two brain systems that govern approach and avoidance behaviors in response to different types of stimuli. The behavioral approach system (BAS) is responsible for mediating reactions to all conditioned and unconditioned appetitive stimuli and is associated with the enhancement of reward or the termination of punishment. The BAS is associated with reward seeking and high levels of BAS activation indicate higher sensitivity to reward dependence and novelty processing (Li et al., 2019). The behavioral inhibition system (BIS) has been postulated to be sensitive to stimuli of punishment or the termination of a reward. The BIS is associated with the avoidance of potentially negative or harmful consequences and high levels of BIS activation imply a proneness to loss avoidance and a tendency to display a blunted response to reward (Li et al., 2019). Although Gray's neuropsychological reinforcement sensitivity theory provided an important view for understanding and explaining addiction, previous results about the associations among BIS/BAS and Internet addiction were inconsistent both among adults and among adolescents. The BIS is neither directly nor indirectly associated with Internet addiction, whereas the BAS is associated with Internet addiction only through depression and social anxiety in adults (Fayazi and Hasani, 2017), while another study found that neither the BAS and nor BIS were related to Internet addiction in adults (Meerkerk et al., 2010). In terms of adolescents, high BAS activation rather than BIS activation could predict the occurrence of Internet addiction (Yen et al., 2012), while another study indicated that the BIS activation not the BAS activation was a significant predictor of Internet addiction (Park et al., 2013). Further, two previous studies reported that both high BAS and high BIS activation were associated with Internet addiction (Giles and Price, 2008; Nam et al., 2018). Although these results from adolescents could indicate that Gray's neuropsychological reinforcement sensitivity theory can help to understand and explain Internet addiction, the inconsistent results require more research to explore the associations between BIS/BAS and Internet addiction. In sum, few studies have explored the roles that impulsivity and BIS/BAS play in Internet addition among adolescents, especially on the basis of the dual-system neurobiological model of addiction. Furthermore, although most previous studies have shown that impulsivity and BIS/BAS contribute to Internet addiction among adolescents, little is known about the mediating and moderating mechanisms underlying these associations.

The Mediating Role of Coping Style

Coping style refers to people's behavioral and cognitive attempts to manage specific external and/or internal demands under stress (Skinner et al., 2003). In general, coping styles can be divided into problem-focused and emotion-focused coping. Problem-focused coping refers to strategies that are directed to address the problems that cause emotional distress (e.g., problem solving, seeking help, and cognitive restructuring), whereas emotion-focused coping refers specifically to strategies that palliate negative emotions (e.g., wishful thinking, denial, and withdrawal behavior) (Compas et al., 2001). Because both coping styles show contextual and process-oriented features, they can change over time and under different circumstances (Schoenmakers et al., 2015). Furthermore, how coping styles are used depends on how an individual interprets the stressor, and different coping styles could cause different results. Taken together, adolescents with high problem-focused coping tend to find appropriate methods to address their difficult circumstances, accompanied by better adjustment (Jackson et al., 2017), while adolescents with high emotion-focused coping tend to avoid their own problems passively, accompanied by maladjustment (Carlo et al., 2012). In previous studies, researchers noted that the two types of coping should be viewed as different constructs of coping instead of opposite poles (Patterson and McCubbin, 1987; Compas et al., 2001). Although there is no direct empirical evidence supporting that coping mediates the relationships among impulsivity, BIS/BAS and Internet addiction in adolescents, some indirect evidence has implied that coping styles play a mediating role in these associations. On one hand, previous studies have found that adolescents with high impulsivity are more likely to use emotion-focused coping but less likely to engage in problem-focused coping (Connor-Smith and Flachsbart, 2007; Lee-Winn et al., 2016). The BAS not the BIS was associated with problem-focused coping, and problem-focused coping mediated the relationship between the BAS and adolescent delinquent behavior, while another study found that emotion-focused coping mediated the relationship between the BIS and adolescent problematic alcohol use (Hasking, 2007; Willem et al., 2012). On the other hand, both high emotion-focused coping and low problem-focused coping were associated with adolescent Internet addiction, while another study found that only emotion-focused coping, not problem-focused coping, increased the risk of Internet addiction in adolescence (Tang et al., 2014; Zhou et al., 2017). Thus, impulsivity and BIS/BAS may be associated with coping styles, which in turn could be associated with Internet addiction. However, to the best of our knowledge, no empirical study has directly explored whether coping styles mediate the relationships among impulsivity, BIS/BAS and adolescent Internet addiction.

The Moderating Role of Gender

Gender is a factor that potentially moderates the links among impulsivity, BIS/BAS, coping styles and Internet addiction. First, previous studies have shown that there are significant gender differences in some of the above variables. For example, men have a relatively higher tendency toward Internet addiction than women in a meta-analysis involving 34 global jurisdictions, suggesting that gender-related differences in Internet availability and social norms could account for the gender differences in Internet addiction (Su et al., 2019). Specifically, greater gender gap in Internet penetration are associated with larger effect sizes of gender differences in Internet addiction ($B = 0.223$, 95% CI: 0.086–0.360). Furthermore, the more the social norms preferentially approve men to involve in potentially addictive behaviors such as smoking and alcohol consumption, the more men exhibit higher tendencies of Internet addiction than women (Su et al., 2019). The prevalence of Internet addiction has been found to be higher in boys than in girls (Ha and Hwang, 2014). Boys have higher impulsivity than girls (Munno et al., 2016). Two previous studies found that women have higher BIS activation and higher activation of specific aspects of the BAS (reward responsiveness) than men (Jorm et al., 1998; Nam et al., 2018). Women were more likely to use emotion-focused coping and less likely to use problem-focused coping than men (Matud, 2004). More importantly, it has been suggested that there are gender differences in the pathway associations between these variables. Compared with girls, Internet addiction has a strong association with impulsivity in boys (Nam et al., 2018). A meta-analysis of 46,025 adolescents found that gender is an important factor that could moderate the relationships between coping styles and Internet addiction in Chinese adolescents (Lei et al., 2018). Furthermore, girls with emotional difficulties were more easily affected by Internet addiction than boys with similar problems (Ha and Hwang, 2014). In addition, according to the social gender role theory, men are socialized as independent and self-reliant while women are socialized as warm, supportive, compassionate, sensitive to the feelings of others, and emotionally expressive (Reevy and Maslach, 2001), which further provides potential evidence for gender as a moderator among impulsivity, BIS/BAS, coping styles and Internet addiction.

The Present Study

The purpose of the present study was to examine how impulsivity and BIS/BAS influence Internet addiction in adolescents. Specifically, this study explored the mediating effects of coping styles on impulsivity, BIS/BAS and Internet addiction as well as the gender differences among these associations. To our knowledge, this is the first comprehensive empirical study incorporating impulsivity, BIS/BAS, coping styles and gender factors and their roles in Internet addiction. On the basis of the dual-system neurobiological model and gender social roles theory (Reevy and Maslach, 2001; Casey et al., 2008), the proposed model is presented in **Figure 1**. It is plausible to hypothesize that coping styles act as mediator among impulsivity, BIS/BAS and Internet addiction, and gender serves as a moderator among these associations in adolescents. More specifically, we want to examine whether the dual-system neurobiological model includes high impulsivity and high BIS in Internet addiction among girls, while the dual-system neurobiological model combines high impulsivity and high BAS in boys. Furthermore, we suggest that emotion-focused coping will play an important role in girls, while problem-focused coping will be central in boys. Therefore, our hypotheses are as follows: (1) boys will report greater Internet addiction than girls; (2) impulsivity and the BIS will positively predict Internet addiction in girls; (3) impulsivity and the BAS will positively predict Internet addiction in boys; (4) emotion-focused coping will serve as a mediator between impulsivity and the BIS with Internet addiction in girls; and (5) problem-focused coping will serve as a mediator between impulsivity and the BAS with Internet addiction in boys.

MATERIALS AND METHODS

Participants and Procedure

According to the rule of thumb approach in the structural equation modeling, 10:1 is the commonly suggested ratio of sample size to free parameters, which is often used for minimum recommendations to determine a sample size for a structural equation modeling test (Bentler and Chou, 1987; Kline, 2016). Because 42 was the largest number of free parameters in our all structural equation models, the sample size was decided to be more than 420 in the present study. A total of 450 Chinese adolescents were recruited from four public schools in Beijing City, China. Among these adolescents, 416 participants ($M_{age} = 14.56$ years, $SD = 1.42$ years, age range: 11–18 years) completed the questionnaires, for a response rate of 92.44%. Thirty-four cases were excluded prior to analysis due to unreturned forms. The sample included 212 girls and 204 boys; 139 (33.41%) of the students were in the 7th grade, 98 (23.56%) in the 8th grade, 102 (24.52%) in the 10th grade, and 77 (18.51%) in the 11th grade. More detailed demographic information was shown in **Table 1**. All participants were fluent in Mandarin.

Ethics Statement

The present study was approved by the Ethics Committee of the Institute of Psychology of the Chinese Academy of Sciences. School approval and parental consent were obtained prior to originating the study. All participants were informed that they could quit the study at any time without being penalized.

Measures

Internet Usage

For each participant, Internet usage information was obtained using 4 questions: (1) "How many years have you used the Internet?" (2) "How many hours do you use the Internet every day?" (3) "What is your duration of online gaming every day?" and (4) "Do you often play online gaming (Yes or No)?"

Young's Diagnostic Questionnaire for Internet Addiction (YDQ)

The YDQ was applied to assess Internet addiction. The YDQ was modified according to the DSM-IV criteria for pathological gambling and consists of 8 "yes" or "no" questions (e.g., "Do you feel the need to use the Internet with increasing amounts of time in order to achieve satisfaction?" and "Do you feel restless, moody, depressed, or irritable when attempting to cut down or stop Internet use?") (Young, 1998). Total scores were calculated according to Young's method, with possible scores for all 8 items

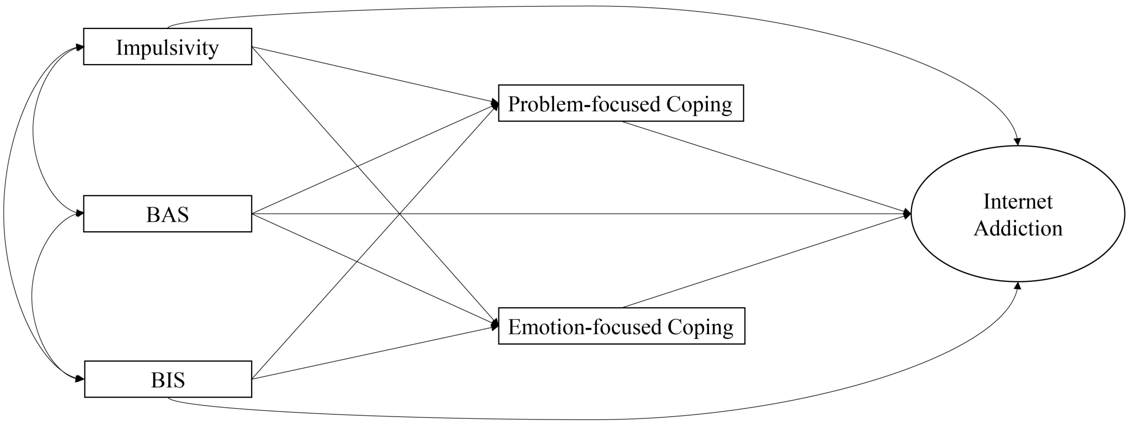

FIGURE 1 | The supposed model.

ranging from 0 to 8. Higher scores reflect a higher level of Internet addiction. Because the YDQ is one of the most widely used questionnaires to evaluate Internet addiction, it has also good reliability and validity in Chinese adolescents (Cao et al., 2007; Li et al., 2014). In the present study, confirmatory factor analysis of the unidimensional model indicated that the model for Internet addiction showed a good fit with the data: $\chi^2/\mathrm{df} = 1.966$, $p < 0.05$; CFI = 0.949, TLI = 0.928, RMSEA = 0.048 and SRMR = 0.041. In the current study, Cronbach's alpha coefficient for Internet addiction was 0.66.

Barratt Impulsiveness Scale (BIS-11)

The BIS-11 is widely used to assess participants' impulsive traits by rating their frequency of 30 items on a scale from 1 (never) to 4 (always) (Patton et al., 1995). The BIS-11 includes three impulsiveness subscales: cognitive key (e.g., "I get easily bored when solving thought problems"), motor key (e.g., "I say things without thinking"), and non-planning key (e.g., "I am more interested in the present than in the future") (Choi J. S. et al., 2014; Martinez-Loredo et al., 2015). The overall impulsiveness score is determined by summing all items, with higher scores denoting greater impulsivity. In the present study, the Chinese version of the BIS-11 was used (Lu et al., 2012), and Cronbach's alpha coefficient was 0.91.

Behavioral Inhibition System/Behavioral Approach System (BIS/BAS) Scales

A validated Chinese version of the BIS/BAS scales was used to assess the BIS and BAS (Li et al., 2015). The BIS/BAS scales are comprised of 20 items in addition to 4 filler items and include the Behavioral Approach System Scale (BAS, 13 items) and the Behavioral Inhibition System Scale (BIS, 7 items) (Carver and White, 1994). The former scale can be divided into three subscales: drive (BAS-drive, 4 items), reward responsiveness (BAS-reward, 5 items), and fun seeking (BAS-fun, 4 items). All items were assessed on a 4-point Likert scale from 1 (totally disagree) to 4 (totally agree). Sample items are "When I see an opportunity for something I like I get excited right away (BAS)" and "Criticism or scolding hurts me quite a bit (BIS)." In the present study, the Cronbach's alpha coefficients of the BAS-drive, BAS-reward, and BAS-fun were 0.67, 0.67, and 0.62, respectively. Scores for all 13 BAS items were summed to yield a single BAS score. Only the total BAS score was used in the current study. The Cronbach's alpha coefficients for the BAS and BIS in the current sample were 0.80 and 0.58, respectively.

Coping Style Scale for Middle School Students

Adolescent coping styles were assessed with the Coping Style Scale for Middle School Students, which has been adapted for the Chinese culture (Dumont and Provost, 1999; Zhou et al., 2017; Sun et al., 2019). This inventory was designed on the basis of Folkman's interaction theory, the self-regulation theory and a prior coping styles questionnaire (Folkman et al., 1986). It is divided into two categories based on coping style, problem-focused coping and emotion-focused coping

TABLE 1 | Descriptive statistics among the variables (*N* = 416).

Variables	**Girls (*N* = 212)**			**Boys (*N* = 204)**			***t*-test**
	Range	***M***	***SD***	**Range**	***M***	***SD***	
Age (years)	12–17	14.52	1.34	11–18	14.61	1.50	−0.67
Education level (years)	7–11	8.67	1.49	7–11	8.75	1.66	−0.49
Network age (years)	0–13	4.94	2.56	0–14	5.06	2.96	−0.44
Internet usage time (hours)	0–10	1.64	1.79	0–14	1.65	2.04	−0.07
Online game time (hours)	0–7	0.36	0.86	0–9	0.88	1.45	−4.36**
Internet addiction	0–8	2.06	1.81	0–8	2.33	1.93	−1.49
Impulsivity	37–131	70.64	14.45	30–147	71.89	16.39	−0.83
BAS	29–52	43.67	5.29	29–52	42.51	5.18	2.24*
BIS	11–28	20.82	3.25	14–28	20.03	2.85	2.63**
Problem-focused coping	35–75	58.62	8.23	19–75	57.01	10.29	1.76
Emotion-focused coping	18–68	40.33	7.94	17–62	39.60	8.01	0.93

*$p < 0.05$; **$p < 0.01$.

(Folkman et al., 1986), and includes 36 items rated on a 4-point Likert scale from 1 (never coping) to 4 (often coping). Problem-focused coping consists of three subscales, including problem solving (7 items, e.g., "I make a plan to solve problems and execute it step by step"), support seeking (7 items, e.g., "I strive to get advice from someone about what to do"), and reasonable explanation (5 items, e.g., "I try to change my perspective to explore the positive side of frustration"). Emotion-focused coping consists of four subscales, including tolerance (4 items, e.g., "My ability is limited, so the only things I can do about unpleasant things is tolerate them"), avoidance (4 items, e.g., "I admit that I can't deal with a problem at hand, so I will give up trying"), venting emotions (4 items, e.g., "I express emotions to reduce my unhappiness"), and fantasy/denial (5 items, e.g., "I say to myself 'this isn't real' when encountering difficulties"). The scale has high construct validity, discrimination validity, and reliability in Chinese adolescents (Chen et al., 2000). In the current study, Cronbach's alpha coefficients for problem-focused coping and emotion-focused coping were 0.88 and 0.79, respectively.

Procedure

The participants were given a packet of questionnaires that included instructions on how to respond to the questions and assurances of anonymity as well as questions regarding their basic demographic information, including gender, age, education grade, BIS/BAS, impulsivity, and coping styles. All scales were administered to participants in their classes. Students were tested individually in their classrooms. All the questionnaires were printed in the Chinese language and took approximately 30 min to finish. No personal identifying information was collected, and all the information collected was confidential.

Data Analysis

Because the proportion of missing data was very low (<1%), mean substitution was adopted to deal with missing data. First, SPSS 20.0 was used to compute descriptive statistics and perform correlation analyses, Chi-square test and *t*-tests. Next, Amos 21.0 was used to test the hypothesized models. Structural equation modeling (SEM) was conducted to test the mediating role of coping styles in the relationships among impulsivity, BIS/BAS and Internet addiction. Furthermore, to assess gender differences, a multi-group (by adolescent gender) SEM was used.

In the present study, several goodness-of-fit indices were used to test the model-data fit. The first one was the Chi-square statistic and its associated *p*-value. If the *p*-value is not significant, it may indicate good model-data fit. However, the Chi-square statistic is sensitive to sample size (Bollen, 1989). Therefore we used the Chi-square to degrees of freedom ratio (χ^2/df) to test model fit. A χ^2/df ratio of less than 3 shows an admissible model fit. Other substitutive indices were also employed in the current study, including the comparative fit index (CFI) (Rigdon, 1996), the Tucker-Lewis Index (TLI) (Tucker and Lewis, 1973), the root mean square error of approximation (RMSEA) (Browne and Cudeck, 1993) and the standardized root mean square residual (SRMR) (Hooper et al., 2008). A CFI and TLI larger than 0.95 and a RMSEA and SRMR less than 0.08 show good model fit (Hooper et al., 2008). For the comparison of the nested models, differences in the χ^2 ($\triangle\chi^2$) and the degree of freedom ($\triangle df$) were used to compare the models with the goodness of fit to determine the model that best fit the data (Satorra, 2000; Byrne and Stewart, 2006). Specifically, the standard of comparison between the two nested models is as follows: when the degrees of freedom increase without a significant increase in the corresponding Chi-square value (that is, $\triangle\chi^2/\triangle df$ is not significant), the better model is the one with a larger degrees of freedom. Otherwise, the smaller degrees of freedom model is better. The predictive and explanatory powers of the model were measured using path coefficients and R^2.

RESULTS

Descriptive Statistics and *t*-Tests/χ^2-Test

The ranges, means and standard deviations of the continuous variables are shown in **Table 1** for girls and boys separately. There were no gender differences in age, education level, network age, Internet usage time, Internet addiction, impulsivity or coping, although boys showed a longer online gaming time. In the present study, 8.5% (n = 18) of girls frequently played online games, while 34.3% (n = 70) of boys frequently played online games. These results indicate that boys are more frequent online gamers than girls (χ^2 = 41.27, $p < 0.001$). Furthermore, BIS/BAS yielded significant gender differences. Compared with girls, boys had lower scores on the BIS and the BAS scales.

Correlation Analyses

Table 2 presents the correlations among the variables in the current study, with girls above the diagonal and boys below the diagonal. For both girls and boys, Internet addiction was positively related to impulsivity, BIS and emotion-focused coping, while Internet addiction was only negatively related to problem-focused coping in boys but had no correlations in girls. For both girls and boys, impulsivity was significantly related to problem-focused coping and emotion-focused coping. There were significant correlations between BAS and both problem-focused coping and emotion-focused coping in boys, but these correlations were not present in girls. For both girls and boys, BIS was positively related to emotion-focused coping but was not significantly related to problem-focused coping. Furthermore, there were significant gender differences in the correlations based on a one-tailed *z*-test, with a stronger association between

TABLE 2 | Associations among the variables for girls and boys.

Variable	1	2	3	4	5	6
Internet addiction	–	0.39**	0.12	0.32**	0	0.38**
Impulsivity	0.36**	–	0.23**	0.22**	−0.24**	0.37**
BAS	0.11	−0.09	–	0.18**	0.12	0.10
4. BIS	0.16*	0.09	0.24**	–	0.07	0.32**
Problem-focused coping	−0.27**	−0.50**	0.30**	0.08	–	0.06
Emotion-focused coping	0.28**	0.37**	0.21**	0.16*	−0.05	–

*BAS, Behavioral Approach System; BIS, Behavioral Inhibition System; *$p < 0.05$; **$p < 0.01$.*

Internet addiction and BIS (*z* difference = 1.73) for girls than for boys ($p < 0.05$), a stronger association between Internet addiction and problem-focused coping (*z* difference = 2.80) for boys than for girls ($p < 0.01$), a stronger association between impulsivity and problem-focused coping (*z* difference = 3.08) for boys than for girls ($p < 0.01$), a stronger association between BAS and problem-focused coping (*z* difference = 1.91) for boys than for girls ($p < 0.05$), and a stronger association between BIS and emotion-focused coping (*z* difference = 1.73) for girls than for boys ($p < 0.05$). The following analyses of the hypothesized models were executed based on the correlation models of these variables.

Structural Equation Model Analyses

Before analyzing the structural equation model, five observed variables (impulsivity, BAS, BIS, problem-focused coping, and emotion-focused coping, representative of their total scores respectively) and one latent variable (Internet addiction) were used to make our model more simplified and efficient. Furthermore, the YDQ was divided into two parcels, where the sum of items 1, 3, 5, and 7 constituted the first parcel (parcel 1), and the sum of items 2, 4, 6, and 8 constituted the second parcel (parcel 2), to act as indicators of Internet addiction employing an item-to-construct balance approach (Little et al., 2002). Then, structural equation modeling with AMOS 21.0 was carried out to examine our hypothesized mediation model. The factor loadings of Internet addiction for parcel 1 and parcel 2 were 0.799 and 0.689, respectively. The results of the model showed a good fit with the data: $\chi^2/df = 2.417$, $p < 0.05$; CFI = 0.984, TLI = 0.935, RMSEA = 0.058 and SRMR = 0.024. To test whether gender moderated the path relationships among these variables, two nested models were estimated. Specifically, we examined whether the estimate of the model parameters (i.e., path coefficients) varied between girls and boys. The first model permitted the structure coefficient of the two models to be estimated freely according to gender, while the second model was administered for the structure path coefficient to be equal. The results showed that these two models were significantly different, $\triangle\chi^2$ (11, N = 416) = 25.424, $p = 0.008$, indicating that they differed according to gender. The structural model displaying unstandardized regression coefficients between variables is presented in **Figure 2**. In addition, we utilized critical ratios of differences (CRDs) as an index to examine the differences in structural path coefficients between genders. If the CRD was larger than 1.96, then the associations between these two variables would demonstrate a significant gender difference at $p < 0.05$. The results showed that the structure path from impulsivity to problem-focused coping revealed a significant gender difference (CRD = 2.48, $p < 0.05$). More specifically, the path coefficient for girls was $\beta = -0.30$, $p < 0.001$, while the path coefficient for boys was $\beta = -0.48$, $p < 0.001$. Thus, compared with girls, impulsivity had a far greater negative influence on problem-focused coping among boys. The structure path from problem-focused coping to Internet addiction also revealed a significant gender difference (CRD = 2.51, $p < 0.05$). More specifically, the path coefficient for girls was $\beta = 0.06$, $p > 0.05$, while the path coefficient for boys was $\beta = -0.25$, $p < 0.01$. Therefore, problem-focused coping had a far greater negative prediction to Internet addiction among boys than among girls. Furthermore, the structure path for the path from BAS to emotion-focused coping revealed a significant gender difference (CRD = −2.73, $p < 0.05$). More specifically, the path coefficient for girls was $\beta = -0.02$, $p > 0.05$, while the path coefficient for boys was $\beta = 0.23$, $p < 0.001$. This result suggests that BAS had a far greater positive impact on emotion-focused coping among boys than among girls. The unstandardized regression coefficients from the multiple-group structural model analysis and the CRDs between girls and boys are presented in **Table 3**. In total, the model explained 32.8% of the variance in Internet addiction among girls and 30.7% of the variance in Internet addiction among boys.

When the final model was chosen, bias-corrected bootstrapping, a non-parametric resampling procedure, was utilized to further test the significance of the mediators. Bootstrapping has considerably greater statistical power to test indirect effects than traditional mediation analyses (MacKinnon et al., 2004). When the 95% confidence intervals (CIs) do not include zero, the indirect effect is statistically significant. In the present study, 5000 bootstrapping samples were generated to derive CIs. The results of the bootstrap analyses indicated that the specific indirect effect of impulsivity on Internet addiction through emotion-focused coping was significant, and the total indirect effects of BIS on Internet addiction and the specific indirect effect of BIS on Internet addiction through emotion-focused coping were also significant in girls. The total indirect effects of impulsivity on Internet addiction and the specific indirect effects of impulsivity on Internet addiction through problem-focused coping or emotion-focused coping were significant, and the specific indirect effect of BAS on Internet addiction through problem-focused coping was also significant in boys (see **Table 4**).

DISCUSSION

Gender Differences in Internet Addiction

Contrary to our hypothesis, we did not find gender differences in Internet addiction, which was in line with the results of McNicol and Thorsteinsson (2017). According to the Internet Availability hypothesis (Mann, 2005), availability is an important determinant of addictive behavior. Men have higher levels of Internet addiction than women, which may be associated in part with gender-related differences in Internet availability (Su et al., 2019). A recent meta-analysis involving 34 global jurisdictions found that the prevalence of Internet addiction in men was only slightly higher than that in women ($g = 0.145$) from a global perspective, and that these gender differences in Internet addiction may be partly caused by the gender-related gaps between in economy and in Internet penetration (Su et al., 2019). The fact that our sample came from the capital of China (Beijing), with a high level of economic development and Internet penetration, may be one of the reasons why there were no gender differences in Internet addiction in the present study. Furthermore, there are no gender differences

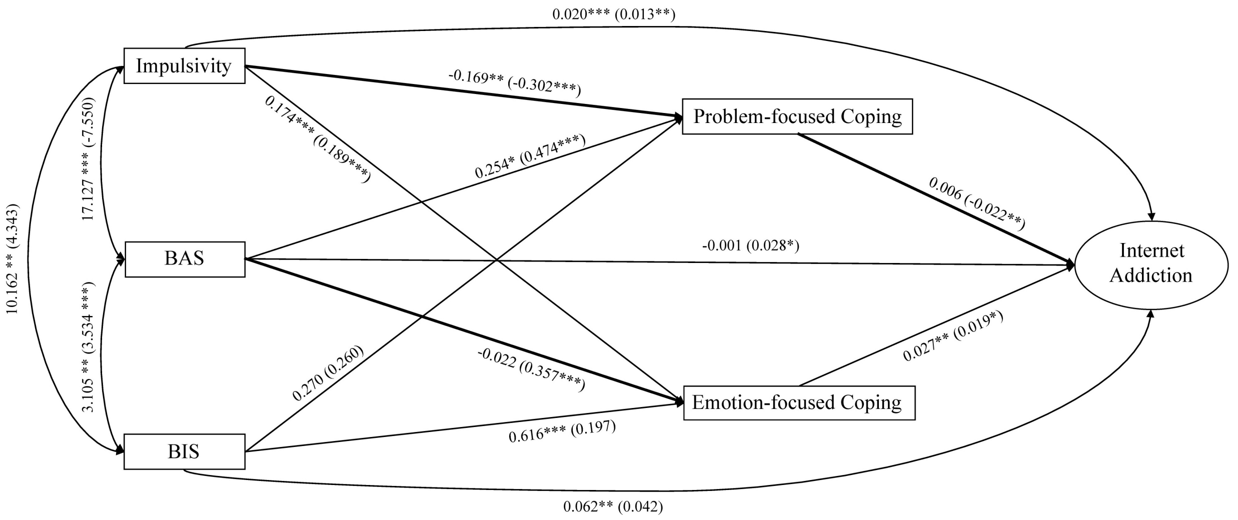

FIGURE 2 | The relationships among impulsivity, BAS, BIS and Internet addiction mediated by coping. Bold lines indicate significant gender differences in these paths. The parameters for girls are displayed outside of the parentheses, while the parameters for boys are denoted within the parentheses. *$p < 0.05$, **$p < 0.01$, and ***$p < 0.001$.

TABLE 3 | Unstandardized coefficients from the multiple-group analysis.

Structural model	Girls estimate (*S.E.*)	Boys estimate (*S.E.*)	CRD
Impulsivity to Internet addiction	0.020 (*0.005*)***	0.013(*0.005*)**	0.933
BAS to Internet addiction	−0.001 (*0.012*)	0.028 (*0.014*)*	−1.549
BIS to Internet addiction	0.062 (*0.021*)**	0.042 (*0.024*)	0.627
Impulsivity to problem-focused coping	−0.169 (*0.039*)***	−0.302 (*0.037*)***	2.484*
BAS to problem-focused coping	0.254 (*0.105*)*	0.474 (*0.120*)***	−1.383
BIS to problem-focused coping	0.270 (*0.172*)	0.260 (*0.217*)	0.038
Impulsivity to emotion-focused coping	0.174 (*0.035*)***	0.189 (*0.031*)***	−0.326
BAS to emotion-focused coping	−0.022 (*0.096*)	0.357 (*0.101*)***	−2.728*
BIS to emotion-focused coping	0.616 (*0.156*)***	0.197 (*0.183*)	1.745
Problem-focused coping to Internet addiction	0.006 (*0.008*)	−0.022 (*0.008*)**	2.509*
Emotion-focused coping to Internet addiction	0.027 (*0.009*)**	0.019 (*0.009*)*	0.644

The numbers in italics in the parentheses represent the standard errors; S.E., standard error; CRD, critical ratio difference.

in network age and total Internet usage time in the present study, which could provide supportive evidence for the Internet Availability hypothesis. In addition, the YDQ was used to assess participants' generalized Internet addiction rather than specific Internet addiction in the current study, which could be another important reason why there were no gender differences in Internet addiction in our sample, because gender may show different effect sizes (magnitude and/or directionality) for specific subtypes of Internet addiction (Su et al., 2019). For example, for online gaming addiction, the rates of men vs. women were 31% vs. 13.1%, while for social networking addiction, the rates of men vs. women were 27.8 and 37.3%, respectively (Tang et al., 2017). Although the gender effect size for generalized Internet addiction was small at 0.15, it was 0.67 for online gaming and 0.10 for social networking sites in a Chinese sample. Meanwhile, there was no significant gender effect size for generalized Internet addiction ($g = -0.03$), but medium gender effect sizes for online gaming ($g = 0.58$) and social networking sites ($g = -0.42$) in a sample from the United States (Tang et al., 2017). In our study, boys spent more time online gaming, and the number of boys who frequently played online games was greater than the number of girls, which could provide some supportive evidence for gender-related differences in subtypes of Internet addiction.

Direct Relations Between Impulsivity and BIS/BAS With Internet Addiction Across Genders

In the current study, we found that impulsivity and BAS could directly positively predict Internet addiction in boys, whereas impulsivity and BIS could directly positively predict Internet addiction in girls. The results in boys could provide supportive evidence for the dual-system neurobiological model that heightened reward-seeking and deficient impulse control may be a risk factor for adolescent addictive behaviors (Casey et al., 2008; Casey and Jones, 2010). Compared with children and

TABLE 4 | The bootstrapping results of the indirect effects in the final model.

Model paths	Standard indirect effects	95% CI	
		Lower	Upper
GIRLS			
Impulsivity→ Internet addiction^a	0.063	−0.028	0.172
Impulsivity → PFC → IA	−0.017	−0.072	0.033
Impulsivity → EFC→ IA	0.080*	0.023	0.168
BAS → Internet addiction^a	0.005	−0.060	0.057
BAS → PFC → IA	0.009	−0.019	0.043
BAS → EFC → IA	−0.004	−0.054	0.032
BIS → Internet addiction^a	0.070*	0.015	0.162
BIS → PFC → IA	0.006	−0.010	0.043
BIS → EFC → IA	0.064*	0.013	0.153
BOYS			
Impulsivity→ Internet addiction^a	0.183**	0.093	0.326
Impulsivity → PFC → IA	0.118*	0.031	0.251
Impulsivity → EFC → IA	0.065*	0.010	0.160
BAS → Internet addiction^a	−0.019	−0.117	0.067
BAS → PFC → IA	−0.058*	−0.142	−0.003
BAS→ EFC → IA	0.039	−0.002	0.101
BIS → Internet addiction^a	−0.006	−0.063	0.041
BIS→ PFC → IA	−0.018	−0.071	0.014
BIS→ EFC → IA	0.012	−0.007	0.068

*^{a}The indirect effect represents the effect through all possible mediators (i.e., problem-focused coping, emotion-focused coping). CI, confidence interval; PFC, problem-focused coping; EFC, emotion-focused coping; IA, Internet addiction. *$p < 0.05$, **$p < 0.01$.*

adults, adolescents are characterized by an imbalance between early emerging "bottom–up" systems that show exaggerated reaction to motivational stimuli and later maturing "top–down" cognitive control systems (Casey and Jones, 2010). Both in boys and in girls, impulsivity is positively correlated to poor to–down cognitive control (Casey and Jones, 2010). Meanwhile, with regard to bottom-up motivational stimuli, boys could be more sensitive to reward stimuli (Steinberg et al., 2009), while girls could be more sensitive to punishment stimuli rather than reward stimuli (Pagliaccio et al., 2016). With the rapid development of the Internet technology, 85.3% of adolescents in China have access to the Internet (China Internet Network Information Center [CNNIC], 2016). As a result, adolescents could seek abundantly available rewarding stimuli conveniently on the Internet. Especially for boys with low cognitive control capacity (high impulsivity), these rewarding stimuli (e.g., online gaming positive incentive) continuously reinforce their Internet behaviors, which gradually increase their risk for Internet addiction. Compared with real world, cyberspace could provide a more convenient, anonymous, and safe social interactions environment. Girls with high BIS, who are more sensitive to punishment stimuli (e.g., criticism or scolding from other people), are prone to overuse of the Internet to "escape loneliness" and "belong to a group" instead of face-to-face interactions or offline activities (Park et al., 2013). Furthermore, low cognitive control capacity (high impulsivity) could deteriorate the negative impact of BIS on Internet use in girls. Thus, girls with high impulsivity and high BIS are more prone to Internet addiction than other girls. Taken together, the present study considers the role of gender in the associations among impulsivity, BIS/BAS and Internet addiction according to the dual-system neurobiological model, which could provide further supportive evidence for the key role of impulsivity on adolescent Internet addiction (Crews and Boettiger, 2009; Brand et al., 2014), and could explain the previous inconsistencies in the associations between BIS/BAS and adolescent Internet addiction (Yen et al., 2012; Park et al., 2013).

Mediating Relations Among Impulsivity, BIS/BAS to Internet Addiction Across Genders

The present study developed a multi-group mediation model to illuminate the different mechanisms underlying the associations of impulsivity and BIS/BAS with Internet addiction between girls and boys. The most important and interesting results showed that different coping styles were an important mechanism through which impulsivity and BIS/BAS were associated with Internet addiction across genders. Specifically, impulsivity and BIS increased the risk of adolescent Internet addiction through enhanced emotion-focused coping in girls. However, impulsivity raised the risk of adolescent Internet addiction through increased emotion-focused coping and decreased problem-focused coping in boys. In addition, problem-focused coping mediated the associations of BAS with Internet addiction in boys. Adolescents have to cope with massive stressors caused by biological, cognitive and social changes that occur across development from childhood to adulthood. The social gender role theory indicates that appraisals of life events might differ across genders (Tamres et al., 2002; Sarrasin et al., 2014). Specifically, compared with men, women are more likely to appraise events as stressful and view stressors as threats rather than challenges. Furthermore, the social gender role theory also indicates that men are socialized as independent, self-reliant and to suppress emotions, while women are socialized as warm, supportive, compassionate, sensitive to the feelings of others, and emotionally expressive with less restrictions (Reevy and Maslach, 2001). Therefore, women are more likely to be accepted by others if they express negative emotions in social interactions than men. Consequently, when the Internet is used as a stress coping resource, girls with high impulsivity and high BIS are more likely to adopt emotion-focused coping (e.g., venting emotions, fantasy, and avoidance) to palliate event-related distress on the Internet, which in turn increases their risk of Internet addiction. These findings are similar to the results of a recent study showing that the combination of impulsivity and neuroticism increases the risk of emotion-focused coping, and thus exacerbates adolescent binge eating behaviors (Keough et al., 2016).

As for boys, when the Internet is used as a stress coping resource, boys with high impulsivity are more likely to use emotion-focused coping (e.g., cyberbullying and avoidance by playing online games) but less likely to engage in problem-focused coping, which is in line with previous studies

(Connor-Smith and Flachsbart, 2007; Lee-Winn et al., 2016). Previous studies have also indicated that a person with emotion-focused coping views Internet use in a more dependent manner (Lam et al., 2009; Milani et al., 2009). The virtual world created by the Internet provides them with an opportunity to escape from external stress and difficulties in real life through short-term pleasure and relief. However, problem-focused coping could decrease the risk of Internet addiction (Al-Gamal et al., 2016). Therefore, more emotion-focused coping and less problem-focused coping increases the risk of Internet addiction.

On the other hand, boys with high BAS have high novelty seeking and fun seeking tendencies (Casey and Jones, 2010), which may cause them to use problem-focused coping frequently in stressful environments. When dealing with the external stress and difficulties that occur in real life, the Internet can be seen as a helpful resource (e.g., acquiring information, seeking others help) instead of as an escape for boys with high BAS. This problem-focused coping could decrease their risk for Internet addiction. Thus, high BAS maybe plays an indirect protective role against Internet addiction in boys, which is similar to the results of Hasking' study showing that reward responsiveness is positively associated with the use of problem-focused coping, which in turn is negatively associated with delinquent behavior in adolescents (Hasking, 2007). Taken together, combined with the direct and indirect relations between BAS and Internet addiction in the present study, these results suggest that BAS is a double-edged sword for Internet addiction in boys, which calls for the need for more studies to understand the beneficial and harmful factors related to BAS in boys.

Implications for Theory and Practice

From a theoretical perspective, extending previous research, the present study provides empirical support for the dual-system neurobiological model among boys in the context of Internet addiction. Furthermore, our study indicates that the combination of deficient impulse control and heightened BIS rather than BAS increases the risk for Internet addiction in girls. To our knowledge, this is the first study to examine the mediating roles of problem-focused and emotion-focused coping from impulsivity and BIS/BAS to Internet addiction and the moderating role of gender among these associations, which is helpful to improve our understanding of Internet addiction among adolescents. It is especially important in cases where Internet addiction is not viewed as a disorder regardless of category by DSM-V because of insufficient evidence (Grant and Chamberlain, 2016). From a practical perspective, our findings may be helpful for providing evidence-based preventions and interventions to decrease Internet addiction among adolescents. In general, further attention should be given to developing Internet addiction prevention and intervention programs that are tailored to the different needs of girls and boys. First, when screening and choosing a target population for further prevention and intervention programs among adolescents, different combinations of risk factors (e.g., impulsivity and BAS in boys) should be adopted according to gender differences. Second, and even more importantly, our results could offer invaluable knowledge on how to prevent and intervene in Internet addiction among adolescents. Specifically, interventions to decrease impulsivity and BIS could have the potential to decrease Internet addiction in girls, while interventions to reduce impulsivity and BAS may have the potential to decrease Internet addiction in boys. In addition, the finding that coping style mediates the associations from impulsivity and BIS/BAS to Internet addiction across genders provides important implications for practice. To prevent and intervene in Internet addiction in adolescents, training techniques should be exploited to enhance adolescents' coping style skills because improving specific behaviors may be more efficient than directly altering individual dispositions (Taylor and Stanton, 2007). On the one hand, parents and practitioners should provide a supportive environment, which could play a positive role in adolescents' coping skills and consequently decrease the risk of Internet addiction in adolescents. On the other hand, coping effectiveness training has previously been confirmed to be an efficient method for improving coping skills (Folkman et al., 1991). Parents and practitioners could adopt methods to help girls decrease their use of emotion-focused coping when managing developmental tasks. In the context of stressors, it would be beneficial to improve the use of problem-focused coping and decrease the use of emotion-focused coping in boys, such as providing boys with the knowledge and practical skills to resolve their problems, seek social support and balance their emotions effectively.

Limitations and Further Directions

Although this study revealed the gender-specific pathways from impulsivity and BIS/BAS to adolescents' Internet addiction, several limitations of the current study merit attention. First, the intention of our study is not to "psychopathologize" adolescence, but rather to explore why some adolescents are more vulnerable to Internet addiction than others. However, because Internet addiction is significantly associated with symptoms of depression, social anxiety, attention-deficit/hyperactivity disorder and other mental disorders, which were not investigated in our sample, future studies including these factors could provide stronger evidence for our results with a high capacity to control for these confounding variables. Second, although YDQ and BIS/BAS scales have good reliability and validity in Chinese adolescents (Cao et al., 2007; Li et al., 2014, 2015), the Cronbach's alpha coefficients for the YDQ and BIS scale were low in the present study, which may be caused by their limited number of items (8 and 7, respectively). Future research should adopt scales with more items to assess Internet addiction and BIS (e.g., the Young's Internet Addiction Test with 20 items; the Sensitivity to Punishment and Sensitivity to Reward Questionnaire with 48 items) (Torrubia et al., 2001; Widyanto and McMurran, 2004). Third, the present study employed a cross-sectional design. Although this study design can demonstrate strong associations among variables, it cannot provide strong evidence of causal relationships among these variables. Therefore, experimental methods and longitudinal designs could be beneficial in future research to provide more reliable conclusions about the directionality of these effects. Finally, more and more research points toward the type of Internet application (e.g., gaming and social networking site) – not the Internet itself – as being responsible for the development of a problematic usage (van Rooij et al., 2010; Lee et al., 2015). However, the type of usage was not considered, which could pose a limitation in the present study. Furthermore, evidence from previous studies has shown that it is very important to distinguish between generalized Internet addiction and specific Internet addiction and that large gender differences exist in online gaming and social networking site use (Montag et al., 2015; Tang et al., 2017; Lopez-Fernandez, 2018). Further studies are needed to include more Internet usage information, which could provide stronger evidence of whether the results of the current study are appropriate for generalized Internet addiction or specific Internet addiction.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Ethics Committee of the Institute of Psychology of the Chinese Academy of Sciences. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

AUTHOR CONTRIBUTIONS

QL and XL designed the study and wrote the protocol. QL and YZ collected the research data. BD conducted the statistical analyses and wrote the manuscript. WD and LW conducted the literature searches and created the figures. All authors approved the final version of the manuscript.

FUNDING

This study was supported by the National Natural Science Foundation of China (Grants 31571161 and 31200782), the Humanities and Social Science Research of the Ministry of Education of China (18YJC190002), the CAS Key Laboratory of Behavioral Science, Institute of Psychology (Y5CX052003), and the China Scholarship Council.

ACKNOWLEDGMENTS

We wish to extend our appreciations to the referees for their comments.

REFERENCES

Al-Gamal, E., Alzayyat, A., and Ahmad, M. M. (2016). Prevalence of internet addiction and its association with psychological distress and coping strategies among university students in jordan. *Perspect. Psychiatr. Care* 52, 49–61. doi: 10.1111/ppc.12102

American Psychiatric Association [APA], (2013). *Diagnostic and Statistical Manual of Mental Disorders (DSM-V)*. Washington, DC: American Psychiatric Press.

Bargeron, A. H., and Hormes, J. M. (2017). Psychosocial correlates of internet gaming disorder: psychopathology, life satisfaction, and impulsivity. *Comput. Hum. Behav.* 68, 388–394. doi: 10.1016/j.chb.2016.11.029

Bentler, P. M., and Chou, C. P. (1987). Practical issues in structural equation modeling. *Sociol. Methods Res.* 16, 187–196. doi: 10.1177/0049124187016001004

Bijttebier, P., Beck, I., Claes, L., and Vandereycken, W. (2009). Gray's reinforcement sensitivity theory as a framework for research on personality-psychopathology associations. *Clin. Psychol. Rev.* 29, 421–430. doi: 10.1016/j.cpr.2009.04.002

Bollen, K. A. (1989). A new incremental fit index for general structural equation models. *Sociol. Methods Res.* 17, 303–316. doi: 10.1177/0049124189017003004

Borca, G., Bina, M., Keller, P. S., Gilbert, L. R., and Begotti, T. (2015). Internet use and developmental tasks: adolescents' point of view. *Comput. Hum. Behav.* 52, 49–58. doi: 10.1016/j.chb.2015.05.029

Brand, M., Laier, C., and Young, K. S. (2014). Internet addiction: coping styles, expectancies, and treatment implications. *Front. Psychol.* 5:1256. doi: 10.3389/fpsyg.2014.01256

Browne, M. W., and Cudeck, R. (1993). "Alternative ways of assessing model fit," in *Testing Structural Equation Models*, SAGE Focus Edn, eds K. A. Bollen, and J. S. Long, (Newbury Park, CA: Sage Publication), 136–162.

Byrne, B. M., and Stewart, S. M. (2006). Teacher's corner: the MACS approach to testing for multigroup invariance of a second-order structure: a walk through the process. *Struct. Equ. Modeling* 13, 287–321. doi: 10.1207/s15328007sem1302_7

Cao, F., Su, L., Liu, T., and Gao, X. (2007). The relationship between impulsivity and internet addiction in a sample of Chinese adolescents. *Eur. Psychiatry* 22, 466–471. doi: 10.1016/j.eurpsy.2007.05.004

Carlo, G., Mestre, M. V., McGinley, M. M., Samper, P., Tur, A., and Sandman, D. (2012). The interplay of emotional instability, empathy, and coping on prosocial and aggressive behaviors. *Pers. Individ. Dif.* 53, 675–680. doi: 10.1016/j.paid.2012.05.022

Carver, C., and White, T. L. (1994). Behavioral inhibition, behavioral activation, and affective responses to impending reward and punishment: the BIS/BAS scales. *J. Pers. Soc. Psychol.* 67, 319–333. doi: 10.1037//0022-3514.67.2.319

Casey, B. J., Getz, S., and Galvan, A. (2008). The adolescent brain. *Dev. Rev.* 28, 62–77. doi: 10.1016/j.dr.2007.08.003

Casey, B. J., and Jones, R. M. (2010). Neurobiology of the adolescent brain and behavior: implications for substance use disorders. *J. Am. Acad. Child Adolesc. Psychiatry* 49, 1189–1201. doi: 10.1016/j.jaac.2010.08.017

Chen, S., Zheng, Q., Pan, J., and Zhen, S. (2000). Preliminary development of coping style scale for middle school students. *Chin. J. Clin. Psychol.* 8, 211–214. doi: 10.1177/1534508408327609

China Internet Network Information Center [CNNIC], (2016). *The Research Report About CHINESE Adolescents' Internet Behavior in 2015* [Online]. Available at: http://www.cnnic.net.cn/hlwfzyj/hlwxzbg/qsnbg/201608/P020160812393489128332.pdf (accessed May 22, 2016).

Choi, J. S., Park, S. M., Roh, M. S., Lee, J. Y., Park, C. B., Hwang, J. Y., et al. (2014). Dysfunctional inhibitory control and impulsivity in internet addiction. *Psychiatry Res.* 215, 424–428. doi: 10.1016/j.psychres.2013.12.001

Choi, S.-W., Kim, H. S., Kim, G.-Y., Jeon, Y., Park, S. M., Lee, J.-Y., et al. (2014). Similarities and differences among Internet gaming disorder, gambling disorder and alcohol use disorder: a focus on impulsivity and compulsivity. *J. Behav. Addict.* 3, 246–253. doi: 10.1556/jba.3.2014.4.6

Choi, K., Son, H., Park, M., Han, J., Kim, K., Lee, B., et al. (2009). Internet overuse and excessive daytime sleepiness in adolescents. *Psychiatry Clin. Neurosci.* 63, 455–462. doi: 10.1111/j.1440-1819.2009.01925.x

Compas, B. E., Connor-Smith, J. K., Saltzman, H., Thomsen, A. H., and Wadsworth, M. E. (2001). Coping with stress during childhood and adolescence: Problems, progress, and potential in theory and research. *Psychol. Bull.* 127, 87–127. doi: 10.1037/0033-2909.127.1.87

Connor-Smith, J. K., and Flachsbart, C. (2007). Relations between personality and coping: a meta-analysis. *J. Pers. Soc. Psychol.* 93, 1080–1107. doi: 10.1037/0022-3514.93.6.1080

Crews, F. T., and Boettiger, C. A. (2009). Impulsivity, frontal lobes and risk for addiction. *Pharmacol. Biochem. Behav.* 93, 237–247. doi: 10.1016/j.pbb.2009.04.018

Dumont, M., and Provost, M. A. (1999). Resilience in adolescents: protective role of social support, coping strategies, self-esteem, and social activities on experience of stress and depression. *J. Youth Adolesc.* 28, 343–363. doi: 10.1023/A:1021637011732

Englund, M. M., Egeland, B., Oliva, E. M., and Collins, W. A. (2008). Childhood and adolescent predictors of heavy drinking and alcohol use disorders in early adulthood: a longitudinal developmental analysis. *Addiction* 103(Suppl. 1), 23–35. doi: 10.1111/j.1360-0443.2008.02174.x

Fayazi, M., and Hasani, J. (2017). Structural relations between brain-behavioral systems, social anxiety, depression and internet addiction: with regard to revised reinforcement sensitivity theory (r-RST). *Comput. Hum. Behav.* 72, 441–448. doi: 10.1016/j.chb.2017.02.068

Folkman, S., Chesney, M., McKusick, L., Ironson, G., Johnson, D. S., and Coates, T. J. (1991). "Translating coping theory into an intervention," in *The Social Context of Coping*, ed. J. Eckenrode, (Boston, MA: Springer US), 239–260. doi: 10.1007/978-1-4899-3740-7_11

Folkman, S., Lazarus, R. S., Gruen, R. J., and DeLongis, A. (1986). Appraisal, coping, health status, and psychological symptoms. *J. Pers. Soc. Psychol.* 50, 571–579. doi: 10.1037/0022-3514.50.3.571

Giles, G., and Price, I. R. (2008). Adolescent computer use: approach, avoidance, and parental control. *Aust. J Psychol.* 60, 63–71. doi: 10.1080/00049530701829896

Grant, J. E., and Chamberlain, S. R. (2016). Expanding the definition of addiction: DSM-5 vs. *ICD*-11. *CNS Spectr.* 21, 300–303. doi: 10.1017/S1092852916000183

Gray, J. A. (1994). "Framework for a taxonomy of psychiatric disorder," in *Emotions-Essays on Emotion Theory*, 1st Edn, eds S. H. M. van Goozen, N. E. Van de Poll, and J. A. Sergeant, (New York, NY: Psychology Press), 32.

Griffiths, M. (2000). Does internet and computer "Addiction" exist? some case study evidence. *Cyberpsychol. Behav.* 3, 211–218. doi: 10.1089/109493100316067

Ha, Y.-M., and Hwang, W. J. (2014). Gender differences in internet addiction associated with psychological health indicators among adolescents using a national web-based survey. *Int. J. Ment. Health Addict.* 12, 660–669. doi: 10.1007/s11469-014-9500-7

Hasking, P. A. (2007). Reinforcement sensitivity, coping, and delinquent behaviour in adolescents. *J. Adolesc.* 30, 739–749. doi: 10.1016/j.adolescence.2006.11.006

Hooper, D., Coughlan, J., and Mullen, M. R. (2008). Structural equation modelling: guidelines for determining model fit. *Electron. J. Bus. Res. Methods* 6, 53–60.

Jackson, Y., Huffhines, L., Stone, K. J., Fleming, K., and Gabrielli, J. (2017). Coping styles in youth exposed to maltreatment: longitudinal patterns reported by youth in foster care. *Child Abuse Negl.* 70, 65–74. doi: 10.1016/j.chiabu.2017.05.001

Jorm, A. F., Christensen, H., Henderson, A. S., Jacomb, P. A., Korten, A. E., and Rodgers, B. (1998). Using the BIS/BAS scales to measure behavioural inhibition and behavioural activation: factor structure, validity and norms in a large community sample. *Pers. Individ. Dif.* 26, 49–58. doi: 10.1016/S0191-8869(98)00143-3

Keough, M. T., Badawi, G., Nitka, D., O'Connor, R. M., and Stewart, S. H. (2016). Impulsivity increases risk for coping-motivated drinking in undergraduates with elevated social anxiety. *Pers. Individ. Dif.* 88, 45–50. doi: 10.1016/j.paid.2015.08.036

Kline, R. B. (2016). *Principles and Practice of Structural Equation Modeling*, 4th Edn. New York, NY: Guilford Press.

Ko, C. H., Yen, J. Y., Chen, C. S., Yeh, Y. C., and Yen, C. F. (2009). Predictive values of psychiatric symptoms for internet addiction in adolescents: a 2-year prospective study. *Arch. Pediatr. Adolesc. Med.* 163, 937–943. doi: 10.1001/archpediatrics.2009.159

Ko, C. H., Yen, J. Y., Yen, C. F., Chen, C. S., and Chen, C. C. (2012). The association between internet addiction and psychiatric disorder: a review of the literature. *Eur. Psychiatry* 27, 1–8. doi: 10.1016/j.eurpsy.2010.04.011

Lam, L. T., Peng, Z. W., Mai, J. C., and Jing, J. (2009). Factors associated with internet addiction among adolescents. *Cyberpsychol. Behav.* 12, 551–555. doi: 10.1089/cpb.2009.0036

Lee, H. W., Choi, J. S., Shin, Y. C., Lee, J. Y., Jung, H. Y., and Kwon, J. S. (2012). Impulsivity in internet addiction: a comparison with pathological gambling. *Cyberpsychol. Behav. Soc. Network.* 15, 373–377. doi: 10.1089/cyber.2012.0063

Lee, Y.-H., Ko, C.-H., and Chou, C. (2015). Re-visiting internet addiction among taiwanese students: a cross-sectional comparison of students' expectations, online gaming, and online social interaction. *J. Abnorm. Child Psychol.* 43, 589–599. doi: 10.1007/s10802-014-9915-4

Lee-Winn, A. E., Townsend, L., Reinblatt, S. P., and Mendelson, T. (2016). Associations of neuroticism-impulsivity and coping with binge eating in a nationally representative sample of adolescents in the United States. *Eat. Behav.* 22, 133–140. doi: 10.1016/j.eatbeh.2016.06.009

Lei, H., Cheong, C. M., Li, S., and Lu, M. (2018). The relationship between coping style and internet addiction among mainland Chinese students: a meta-analysis. *Psychiatry Res.* 270, 831–841. doi: 10.1016/j.psychres.2018.10.079

Li, J., Li, D., Jia, J., Li, X., Wang, Y., and Li, Y. (2018). Family functioning and internet addiction among adolescent males and females: a moderated mediation analysis. *Child. Youth Serv. Rev.* 91, 289–297. doi: 10.1016/j.childyouth.2018.06.032

Li, Q., Wang, Y., Yang, Z., Dai, W., Zheng, Y., Sun, Y., et al. (2019). Dysfunctional cognitive control and reward processing in adolescents with Internet gaming disorder. *Psychophysiology* e13469. doi: 10.1111/psyp.13469 [Epub ahead of print].

Li, W., Zhang, W., Xiao, L., and Nie, J. (2016). The association of internet addiction symptoms with impulsiveness, loneliness, novelty seeking and behavioral inhibition system among adults with attention-deficit/hyperactivity disorder (ADHD). *Psychiatry Res.* 243, 357–364. doi: 10.1016/j.psychres.2016.02.020

Li, Y., Guan, Y., Wang, F., Zhou, X., Guo, K., Jiang, P., et al. (2015). Big-five personality and BIS/BAS traits as predictors of career exploration: the mediation role of career adaptability. *J. Vocat. Behav.* 89, 39–45. doi: 10.1016/j.jvb.2015.04.006

Li, Y., Zhang, X., Lu, F., Zhang, Q., and Wang, Y. (2014). Internet addiction among elementary and middle school students in China: a nationally representative sample study. *Cyberpsychol. Behav. Soc. Network.* 17, 111–116. doi: 10.1089/cyber.2012.0482

Little, T., Cunningham, W., Shahar, G., and Widaman, K. (2002). To parcel or not to parcel: exploring the question, weighing the merits. *Struct. Equ. Model. A Multidiscip. J.* 9, 151–173. doi: 10.1207/S15328007SEM0902_1

Lopez-Fernandez, O. (2018). Generalised versus specific internet use-related addiction problems: a mixed methods study on internet, gaming, and social networking behaviours. *Int. J. Environ. Res. Public Health* 15:E2913. doi: 10.3390/ijerph15122913

Lu, J., Kurths, J., Cao, J., Mahdavi, N., and Huang, C. (2012). Synchronization control for nonlinear stochastic dynamical networks: pinning impulsive strategy. *IEEE Trans. Neural Netw. Learn. Syst.* 23, 285–292. doi: 10.1109/TNNLS.2011.2179312

MacKinnon, D. P., Lockwood, C. M., and Williams, J. (2004). Confidence limits for the indirect effect: distribution of the product and resampling methods. *Multivariate Behav. Res.* 39, 99–128. doi: 10.1207/s15327906mbr3901_4

Mann, R. E. (2005). Availability as a low of addiction. *Addiction* 100, 924–925. doi: 10.1111/j.1360-0443.2005.01147.x

Martinez-Loredo, V., Fernandez-Hermida, J. R., Fernandez-Artamendi, S., Carballo, J. L., and Garcia-Rodriguez, O. (2015). Spanish adaptation and validation of the barratt impulsiveness scale for early adolescents (BIS-11-A). *Int. J. Clin. Health Psychol.* 15, 274–282. doi: 10.1016/j.ijchp.2015.07.002

Matud, M. P. (2004). Gender differences in stress and coping styles. *Pers. Individ. Dif.* 37, 1401–1415. doi: 10.1016/j.paid.2004.01.010

McNicol, M. L., and Thorsteinsson, E. B. (2017). Internet addiction, psychological distress, and coping responses among adolescents and adults. *Cyberpsychol. Behav. Soc. Network.* 20, 296–304. doi: 10.1089/cyber.2016.0669

Meerkerk, G. J., van den Eijnden, R. J. J. M., Franken, I. H. A., and Garretsen, H. F. L. (2010). Is compulsive internet use related to sensitivity to reward and punishment, and impulsivity? *Comput. Hum. Behav.* 26, 729–735. doi: 10.1016/j.chb.2010.01.009

Milani, L., Osualdella, D., and Di Blasio, P. (2009). Quality of interpersonal relationships and problematic internet use in adolescence. *Cyberpsychol. Behav.* 12, 681–684. doi: 10.1089/cpb.2009.0071

Montag, C., Bey, K., Sha, P., Li, M., Chen, Y. F., Liu, W. Y., et al. (2015). Is it meaningful to distinguish between generalized and specific Internet addiction? Evidence from a cross-cultural study from Germany, Sweden, Taiwan and China. *Asia Pac. Psychiatry* 7, 20–26. doi: 10.1111/appy.12122

Morrison, C. M., and Gore, H. (2010). The relationship between excessive internet use and depression: a questionnaire-based study of 1,319 young people and adults. *Psychopathology* 43, 121–126. doi: 10.1159/000277001

Munno, D., Saroldi, M., Bechon, E., Sterpone, S. C., and Zullo, G. (2016). Addictive behaviors and personality traits in adolescents. *CNS Spectr.* 21, 207–213. doi: 10.1017/S1092852915000474

Nam, C. R., Lee, D. H., Lee, J. Y., Choi, A. R., Chung, S. J., Kim, D. J., et al. (2018). The role of resilience in internet addiction among adolescents between sexes: a moderated mediation model. *J. Clin. Med.* 7:222. doi: 10.3390/jcm7080222

Pagliaccio, D., Luking, K. R., Anokhin, A. P., Gotlib, I. H., Hayden, E. P., Olino, T. M., et al. (2016). Revising the BIS/BAS Scale to study development: Measurement invariance and normative effects of age and sex from childhood through adulthood. *Psychol. Assess.* 28, 429–442. doi: 10.1037/pas0000186

Park, S. M., Park, Y. A., Lee, H. W., Jung, H. Y., Lee, J.-Y., and Choi, J.-S. (2013). The effects of behavioral inhibition/approach system as predictors of Internet addiction in adolescents. *Pers. Individ. Dif.* 54, 7–11. doi: 10.1016/j.paid.2012.07.033

Patterson, J. M., and McCubbin, H. I. (1987). Adolescent coping style and behaviors: conceptualization and measurement. *J. Adolesc.* 10, 163–186. doi: 10.1016/S0140-1971(87)80086-6

Patton, J. H., Stanford, M. S., and Barratt, E. S. (1995). Factor structure of the Barratt impulsiveness scale. *J. Clin. Psychol.* 51, 768–774. doi: 10.1002/1097-4679(199511)51:6<768::AID-JCLP2270510607>3.0.CO;2-1

Przepiorka, A., Blachnio, A., and Cudo, A. (2019). The role of depression, personality, and future time perspective in internet addiction in adolescents and emerging adults. *Psychiatry Res.* 272, 340–348. doi: 10.1016/j.psychres.2018.12.086

Reevy, G. M., and Maslach, C. (2001). Use of social support: gender and personality differences. *Sex Roles* 44, 437–459. doi: 10.1023/A:1011930128829

Rigdon, E. E. (1996). CFI versus RMSEA: a comparison of two fit indexes for structural equation modeling. *Struct. Equ. Modeling* 3, 369–379. doi: 10.1080/10705519609540052

Robbins, T. W., Gillan, C. M., Smith, D. G., de Wit, S., and Ersche, K. D. (2012). Neurocognitive endophenotypes of impulsivity and compulsivity: towards dimensional psychiatry. *Trends Cogn. Sci.* 16, 81–91. doi: 10.1016/j.tics.2011.11.009

Rubia, K., Overmeyer, S., Taylor, E., Brammer, M., Williams, S., Simmons, A., et al. (2000). Functional frontalisation with age: mapping neurodevelopmental trajectories with fMRI. *Neurosci. Biobehav. Rev.* 24, 13–19. doi: 10.1016/S0149-7634(99)00055-X

Rubia, K., Smith, A. B., Woolley, J., Nosarti, C., Heyman, I., Taylor, E., et al. (2006). Progressive increase of frontostriatal brain activation from childhood to adulthood during event-related tasks of cognitive control. *Hum. Brain Mapp.* 27, 973–993. doi: 10.1002/hbm.20237

Salmela-Aro, K., Upadyaya, K., Hakkarainen, K., Lonka, K., and Alho, K. (2017). The dark side of internet use: two longitudinal studies of excessive internet use, depressive symptoms, school burnout and engagement among finnish early and late adolescents. *J. Youth Adolesc.* 46, 343–357. doi: 10.1007/s10964-016-0494-2

Sarrasin, O., Mayor, E., and Faniko, K. (2014). Gender traits and cognitive appraisal in young adults: the mediating role of locus of control. *Sex Roles* 70, 122–133. doi: 10.1007/s11199-013-0336-6

Satorra, A. (2000). "Scaled and adjusted restricted tests in multi-sample analysis of moment structures," in *Innovations in Multivariate Statistical Analysis: A Festschrift for Heinz Neudecker*, eds R. D. H. Heijmans, D. S. G. Pollock, and A. Satorra, (Boston, MA: Springer US), 233–247. doi: 10.1007/978-1-4615-4603-0_17

Schoenmakers, E. C., van Tilburg, T. G., and Fokkema, T. (2015). Problem-focused and emotion-focused coping options and loneliness: how are they related? *Eur. J. Age.* 12, 153–161. doi: 10.1007/s10433-015-0336-1

Shapira, N. A., Goldsmith, T. D., Keck, P. E. J., Khosla, U. M., and McElroy, S. L. (2000). Psychiatric features of individuals with problematic internet use. *J. Affect. Disord.* 57, 267–272. doi: 10.1016/S0165-0327(99)00107-X

Shaw, M., and Black, D. W. (2008). Internet addiction definition, assessment, epidemiology and clinical management. *CNS Drugs* 22, 353–365. doi: 10.2165/00023210-200822050-00001

Sim, T., Gentile, D. A., Bricolo, F., Serpelloni, G., and Gulamoydeen, F. (2012). A conceptual review of research on the pathological use of computers, video games, and the internet. *Int. J. Ment. Health Addict.* 10, 748–769. doi: 10.1007/s11469-011-9369-7

Skinner, E. A., Edge, K., Altman, J., and Sherwood, H. (2003). Searching for the structure of coping: a review and critique of category systems for classifying ways of coping. *Psychol. Bull.* 129, 216–269. doi: 10.1037/0033-2909.129.2.216

Somerville, L. H., and Casey, B. J. (2010). Developmental neurobiology of cognitive control and motivational systems. *Current Opinion in Neurobiology* 20, 236–241. doi: 10.1016/j.conb.2010.01.006

Spada, M. M. (2014). An overview of problematic internet use. *Addict. Behav.* 39, 3–6. doi: 10.1016/j.addbeh.2013.09.007

Stavropoulos, V., Kuss, D. J., Griffiths, M. D., Wilson, P., and Motti-Stefanidi, F. (2017). MMORPG gaming and hostility predict internet addiction symptoms in adolescents: an empirical multilevel longitudinal study. *Addict. Behav.* 64, 294–300. doi: 10.1016/j.addbeh.2015.09.001

Steinberg, L. (2008). A social neuroscience perspective on adolescent risk-taking. *Dev. Rev.* 28, 78–106. doi: 10.1016/j.dr.2007.08.002

Steinberg, L. (2010). A dual systems model of adolescent risk-taking. *Dev. Psychobiol.* 52, 216–224. doi: 10.1002/dev.20445

Steinberg, L., Graham, S., O'Brien, L., Woolard, J., Cauffman, E., and Banich, M. (2009). Age differences in future orientation and delay discounting. *Child Dev.* 80, 28–44. doi: 10.1111/j.1467-8624.2008.01244.x

Su, W., Han, X., Jin, C., Yan, Y., and Potenza, M. N. (2019). Are males more likely to be addicted to the internet than females? A meta-analysis involving 34 global jurisdictions. *Comput. Hum. Behav.* 99, 86–100. doi: 10.1016/j.chb.2019.04.021

Sun, J., Liu, Q., and Yu, S. (2019). Child neglect, psychological abuse and smartphone addiction among Chinese adolescents: the roles of emotional intelligence and coping style. *Comput. Hum. Behav.* 90, 74–83. doi: 10.1016/j.chb.2018.08.032

Tamm, L., Menon, V., and Reiss, A. L. (2002). Maturation of brain function associated with response inhibition. *J. Am. Acad. Child Adolesc. Psychiatry* 41, 1231–1238. doi: 10.1097/00004583-200210000-00013

Tamres, L. K., Janicki, D., and Helgeson, V. S. (2002). Sex differences in coping behavior: a meta-analytic review and an examination of relative coping. *Pers. Soc. Psychol. Rev.* 6, 2–30. doi: 10.1207/s15327957pspr0601_1

Tang, C. S., Koh, Y. W., and Gan, Y. (2017). Addiction to internet use, online gaming, and online social networking among young adults in china, singapore, and the United States. *Asia Pac. J. Public Health* 29, 673–682. doi: 10.1177/1010539517739558

Tang, J., Yu, Y., Du, Y., Ma, Y., Zhang, D., and Wang, J. (2014). Prevalence of internet addiction and its association with stressful life events and psychological symptoms among adolescent internet users. *Addict. Behav.* 39, 744–747. doi: 10.1016/j.addbeh.2013.12.010

Taylor, S. E., and Stanton, A. L. (2007). Coping resources, coping processes, and mental health. *Annu. Rev. Clin. Psychol.* 3, 377–401. doi: 10.1146/annurev.clinpsy.3.022806.091520

Torrubia, R., Ávila, C., Moltó, J., and Caseras, X. (2001). The sensitivity to punishment and sensitivity to reward questionnaire (SPSRQ) as a measure of Gray's anxiety and impulsivity dimensions. *Pers. Individ. Dif.* 31, 837–862. doi: 10.1016/S0191-8869(00)00183-5

Tucker, L. R., and Lewis, C. (1973). A reliability coefficient for maximum likelihood factor analysis. *Psychometrika* 38, 1–10. doi: 10.1007/BF02291170

van Rooij, A. J., Schoenmakers, T. M., van de Eijnden, R. J. J. M., and van de Mheen, D. (2010). Compulsive internet use: the role of online gaming and other internet applications. *J. Adolesc. Health* 47, 51–57. doi: 10.1016/j.jadohealth.2009.12.021

Widyanto, L., and McMurran, M. (2004). The psychometric properties of the internet addiction test. *Cyberpsychol. Behav.* 7, 443–450. doi: 10.1089/cpb.2004.7.443

Willem, L., Bijttebier, P., Claes, L., and Uytterhaegen, A. (2012). Temperament and problematic alcohol use in adolescence: an examination of drinking motives as mediators. *J. Psychopathol. Behav. Assess.* 34, 282–292. doi: 10.1007/s10862-012-9279-4

World Health Organization [WHO], (2018). *ICD-11 Beta Draft - Mortality and Morbidity Statistics. Mental, Behavioural or Neurodevelopmental disorders.* [Online]. Geneva: World Health Organization.

Wu, A. M., Cheung, V. I., Ku, L., and Hung, E. P. (2013). Psychological risk factors of addiction to social networking sites among Chinese smartphone users. *J. Behav. Addict.* 2, 160–166. doi: 10.1556/JBA.2.2013.006

Yen, J. Y., Cheng-Fang, Y., Chen, C. S., Chang, Y. H., Yeh, Y. C., and Ko, C. H. (2012). The bidirectional interactions between addiction, behaviour approach and behaviour inhibition systems among adolescents in a prospective study. *Psychiatry Res.* 200, 588–592. doi: 10.1016/j.psychres.2012.03.015

Young, K. S. (1998). Internet addiction: the emergence of a new clinical disorder. *Cyberpsychol. Behav.* 1, 237–244. doi: 10.1089/cpb.1998.1.237

Yurgelun-Todd, D. (2007). Emotional and cognitive changes during adolescence. *Curr. Opin. Neurobiol.* 17, 251–257. doi: 10.1016/j.conb.2007.03.009

Zhang, Y., Mei, S., Li, L., Chai, J., Li, J., and Du, H. (2015). The relationship between impulsivity and internet addiction in chinese college students: a moderated mediation analysis of meaning in life and self-esteem. *PLoS One* 10:e0131597. doi: 10.1371/journal.pone.0131597

Zhou, Y., Li, D., Li, X., Wang, Y., and Zhao, L. (2017). Big five personality and adolescent internet addiction: the mediating role of coping style. *Addict. Behav.* 64, 42–48. doi: 10.1016/j.addbeh.2016.08.009

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Neuroscience

ORIGINAL RESEARCH
published: 25 October 2019
doi: 10.3389/fnins.2019.01162

Your Performance Is My Concern: A Perspective-Taking Competition Task Affects ERPs to Opponent's Outcomes

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Previous research has shown that people have more empathic responses to in-group members and more schadenfreude to out-group members. As a dimension of cognitive empathy, perspective-taking has been considered to be related to the enhancement of empathy. We tried to combine these effects through manipulation of a competitive task with opponents and an in-group partner and investigated the potential effect of in-group bias or the perspective-taking effect on outcome evaluation. We hypothesized that the neural activities would provide evidence of in-group bias. We tested it with a simple gambling observation task and recorded subjects' electroencephalographic (EEG) signals. Our results showed that the opponent's loss evoked larger feedback-related negativity (FRN) and smaller P300 activity than the partner's loss condition, and there was a win vs. loss differential effect in P300 for the opponent only. The principal component analysis (PCA) replicated the loss vs. win P300 effect to opponent's performance. Moreover, the correlation between the inclusion of the other in the self (IOS) scores and FRN suggests perspective-taking may induce greater monitoring to opponent's performance, which increases the win vs. loss differentiation brain response to the out-group agent. Our results thus provide evidence for the enhanced attention toward out-group individuals after competition manipulation, as well as the motivation significance account of FRN.

Keywords: in-group bias, gambling task, feedback related negativity, P300, EEG

Edited by:
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Specialty section:
This article was submitted to
Decision Neuroscience,
a section of the journal
Frontiers in Neuroscience

Received: *30 May 2019*
Accepted: *14 October 2019*
Published: *25 October 2019*

Citation:
Yu H, Nan W, Yang G, Li Q, Wu H and Liu X (2019) Your Performance Is My Concern: A Perspective-Taking Competition Task Affects ERPs to Opponent's Outcomes. Front. Neurosci. 13:1162. doi: 10.3389/fnins.2019.01162

INTRODUCTION

As an important aspect of self-representation in social life, the in-group bias refers to the behavioral pattern of people more favoring in-group members than out-group members, which also has been widely explored from both developmental and evolutionary views (Brewer, 1979; Struch and Schwartz, 1989; Van Bavel et al., 2008; Yang et al., 2014; Oestereich et al., 2019). Using a minimal group paradigm, Tajfel (1970) and Tajfel et al. (1971) found that even random group classification could elicit in-group bias and out-group discrimination in subjects. A large number of social psychology studies reported the in-group bias or intergroup discrimination respectively from different aspects, such as, developmental and evolutionary views (Brewer, 1979;

Struch and Schwartz, 1989; Van Bavel et al., 2008; Yang et al., 2014; Oestereich et al., 2019). Such in-group bias or out-group discrimination modulates various people's social behaviors, including both helpful and harmful behaviors (Cikara et al., 2011, 2014; Dickinson et al., 2018).

Apart from social psychology studies, neuroscientific research has also provided evidence for the effect of group identity on people's emotions or action tendency. Studies have shown that racial group membership modulates brain activities in a pain empathy task (Xu et al., 2009; Contreras-Huerta et al., 2013; Fabi and Leuthold, 2018; Han, 2018). Montalan et al. (2012) adopted Minimal Group Paradigm (participants were randomly assigned to different groups: e.g., underestimator and overestimator group in the dot estimation task) to investigate the empathy preference, and found higher pain empathy to in-group members and lower empathy to out-group members in imagined pain empathy condition. Such brain activity of empathy has been shown to be able to predict the altruism motivation (Mathur et al., 2010; Xin et al., 2018) or costly helping (Hein et al., 2010; Preis et al., 2013). Moreover, as an interesting intergroup emotion, schadenfreude (Dasborough and Harvey, 2017) has also been found in neuroscience (Steinbeis and Singer, 2014; Vollberg and Cikara, 2018). One representative work from Cikara et al. (2011) on soccer fans showed that the win of the favorite team (in-group) and the loss of the rival team (out-group) activate the ventral striatum, which is a reward-related brain region. Taken together, both social psychology and neuroimaging studies indicate that in-group bias has an impact on empathy and intergroup schadenfreude.

Previous studies from Sherif showed competition is a key element in group differentiation (Sherif et al., 1961; Sherif, 1966). Previous group manipulations usually involved competition tasks. For example, studies from Molenberghs (Molenberghs et al., 2012; Morrison et al., 2012) used a team competition task in which participants had to respond as quickly as possible after the "GO" signal. In that case, people do not need to face the opponent directly and interact with them. However, people usually need to anticipate their opponents' mind in the competition situation. Notably, the empathy level is highly correlated with perspective-taking, which is considered as a key cognitive component of empathy (Davis et al., 1996). Perspective-taking is also a way to reduce intergroup conflicts and improve the intergroup relationship (Cohen and Insko, 2008; Shih et al., 2009; Todd et al., 2011; Böhm et al., 2018). For instance, a study showed that a perspective-taking viewing task improved subjects' liking and induced more empathic feelings toward another member of the out-group (Shih et al., 2009). Such an intergroup relationship improvement effect from perspective-taking may be attributable to the formation of a "social bond" (Mcdonald et al., 2017). However, how a perspective-taking competition game affects the in-group or out-group's outcome processing has not been investigated. Therefore, the present study will investigate the outcome evaluation by group membership and perspective-taking competition game manipulation.

Works in the domain of outcome evaluation have identified two key related ERP components: the feedback-related negativity (FRN) and the P300 (Osinsky et al., 2016). FRN is a fronto-central negative deflection that is larger following the presentation of negative feedback (Miltner et al., 1997; Holroyd and Coles, 2002; Hajcak et al., 2005). However, other recent studies have suggested that the FRN can be conceptualized as a positive deflection that is more positive following a reward compared with non-reward outcomes, particularly by principal component analysis (PCA) ERP studies (Holroyd et al., 2008; Foti et al., 2011). FRN is thought to be associated with reward prediction errors in reinforcement learning theory (Holroyd and Coles, 2002; Yeung and Sanfey, 2004), which was challenged by a study showing that FRN reflects the salience errors (Talmi et al., 2013) or expectation (Cao et al., 2015). Further, the P300 component, which is traditionally considered as reflecting the attention process or context-updating (Zhao et al., 2017), has also been suggested to be associated with the motivational significance of reward (Wu and Zhou, 2009) or the valence of the outcome (Hajcak et al., 2005).

Interestingly, studies also showed a "mirror" performance monitoring system in which observing another's gain or loss also evokes similar FRN, which is called observational FRN (oFRN), as it applies in observation situations (Kang et al., 2010; Wang Y. et al., 2014). Fukushima and Hiraki (2009) found that significant oFRN was elicited only when humans were in observation, not computer players. Further, researchers have investigated the effect of an interpersonal relationship through the ERP correlating to outcome evaluation (Itagaki and Katayama, 2008; Leng and Zhou, 2010; Marco-Pallares et al., 2010). For example, Leng and Zhou explored the different neural responses to friends and strangers when the observer was engaged in the same gambling game and failed to find a differentiation of FRN responses between friends and strangers observations. In another study, they found FRN and P300 responses to win and loss feedbacks similarly increased (Zhou et al., 2010). In summary, FRN and P300 are considered as neural markers for empathy toward an outcome evaluation (Miltner et al., 2003; Fukushima and Hiraki, 2009). However, as far as we know, there has been no study combining group membership and perspective-taking manipulation to examine these effects on outcome empathy.

In the present study, we manipulated a temporary group identity in a competition context and utilized an interactive football game to increase the perspective-taking toward the out-group members. Then we examined the possible differential effect on the partner's and opponent's win or loss in a benefit-independent context. It sounds that the in-group member's outcome evoked a larger "empathy" effect due to in-group favoritism. However, as Galinsky et al. (2008) wrote, "*understanding one's opponent is valuable for success in competitive interactions*" and "*get inside the head of your opponent*" is crucial for social interaction. Following this view, we also expect enhanced attention regarding an out-group member's outcome. Therefore, we asked an open question regarding which effect (in-group favoritism or perspective-taking) is more prominent in a simple "gambling observing" task. We aimed to examine two possible effects: the in-group empathy bias effect (e.g., more concern about a partner's outcome or an opponent's loss per the schadenfreude effect) and the competition induced attention on opponent effect (e.g., more concern to an opponent's outcome for the interaction in a perspective-taking competition game).

MATERIALS AND METHODS

Participants

Nineteen right-handed man college students with normal vision (age: 22.90 ± 0.93) from Beijing participated in this study. All participants were recruited through advertisement, with no history of neurological or psychiatric illness and no drug intake. To control the task familiarity, all participants reported have the experience of watching football matches. All procedures were approved by the institutional review boards (IRB) of the Institute of Psychology, Chinese Academy of Sciences. All participants signed the informed consent before the experiment and were paid after the experiment.

Procedure

The interpersonal reactivity index (IRI) and the inclusion of others in the self (IOS) scale data were collected before the experimental procedure. Before the formal experimental procedure, participants were told that they would join this experiment with other three participants (actually experimenters) at the same time. To make the real participants believe this, we called them and emphasized the experiment time to make sure that everybody arrived on time in case of meeting the other experimenters in the building. Before the formal procedure, all participants were asked to take a look at the other experiment rooms, with or without participants there. Moreover, we asked them to wait for 1–2 min before the first stage if one player was late.

The formal procedure consisted of three stages, as is illustrated in **Figure 1**.

Gambling Observation Stage

Participants were instructed that two players (the partner and one opponent) were randomly selected to participate in the gambling task, and the remaining two players needed to observe their performance. All four players practiced the gambling task and understood that the gain or loss was independent (i.e., win or loss for yourself). For observers, they are asked to answer one question to ensure their involvement in the task. The question is about who would win more money in the gambling task. The one with the correct answer will be awarded 10 Yuan. For each trial of the observation task, the face of the gambling player was presented for 900 ms, implying the one performing the gambling task in the current trial. Then the gambling task started with a fixation for 300 ms, then two cards were presented (two white rectangles with a 2.5° × 2.5° visual angle), and the player was asked to make a selection by pressing the "F" or "J" key. Feedback was presented for 1000 ms at the end of the trial (see **Figure 1C**). The probability of win/loss was equal across the partner and opponent to rule out potential confounding influences on the differential win–loss probability. There were 200 trials (50 trials for each condition: partner-win, partner-loss, opponent-win, and opponent-loss) in total, with a short break for every 40 trials in the task. The whole gambling observation task lasted around 30 min.

In the formal procedure, all instructions were presented through PowerPoint software. All aforementioned procedures were conducted by E-Prime software (Version 2.0, Psychology Software Tools, Inc.). After completing all formal procedures, participants were asked to rate the performance on a seven-point scale of all players in the tasks (foot task and gambling task). After receiving payment, the participants were also asked to report their involvement or seriousness in the observation task on an assumed 7 point scale.

Post-experiment Rating

After the experiment, participants were instructed to recall some experimental details and provide ratings about their feelings of happiness when the other's win or loss outcome occurred. All participants made a correct recall of their performance in the experiment, and they were paid 10 Yuan by Alipay for their completion of this rating task.

Electroencephalographic Recording and Preprocessing

During the task, the participant sat approximately 80 cm from a computer screen comfortably in an electrically shielded room. We recorded the electroencephalographic (EEG) data using a 64-channel Neuroscan system (Neuroscan Inc., Herndon, VA, United States) in the gambling observation sessions. Raw EEG data were sampled at 500 Hz/channel, referenced to the left mastoid on-line, with impedance lower than 5 kΩ. Vertical electrooculograms (VEOG) were recorded supra- and infra-orbitally at the left eye. Horizontal EOGs (HEOG) were recorded by electrodes at the left and right orbital rims. The online continuous data were digitized with a bandpass of 0.05–100 Hz.

Electroencephalographics were re-referenced to the average of the left and right mastoids and filtered with a low pass of 20 Hz (24 dB/oct) off-line (Hajcak et al., 2006). Epochs were feedback-locked, from 100 ms before the feedback onset to 500 ms after the feedback onset. Ocular artifacts were removed from the EEGs using a regression procedure implemented with Neuroscan software (Scan 4.5). Trials exceeding the threshold of ±80 μV were excluded from further analysis. As a result, 13.4% of the epochs were rejected across participants. Trials of four conditions (partner-win, partner-loss, opponent-win, and opponent-loss) were averaged, respectively, and a −100 to 0 ms baseline was used to perform a baseline correction.

Average ERP Analysis

Previous literature identified FRN by creating a difference wave between win and loss trials (Dunning and Hajcak, 2007; Leng and Zhou, 2010) or from the grand-averaged waveform (Luo et al., 2014). In our study, we are interested in the group effect on ERPs in both the win and the loss conditions. Therefore, we directly measured the FRN and P300 in the grand-averaged waveforms rather than the difference wave. The grand-averaged ERPs at FCz and CPz and the corresponding topography map are presented in **Figure 2**. Based on both the previous literature (Gu et al., 2011) and visual inspection of the topography map, the FRN was

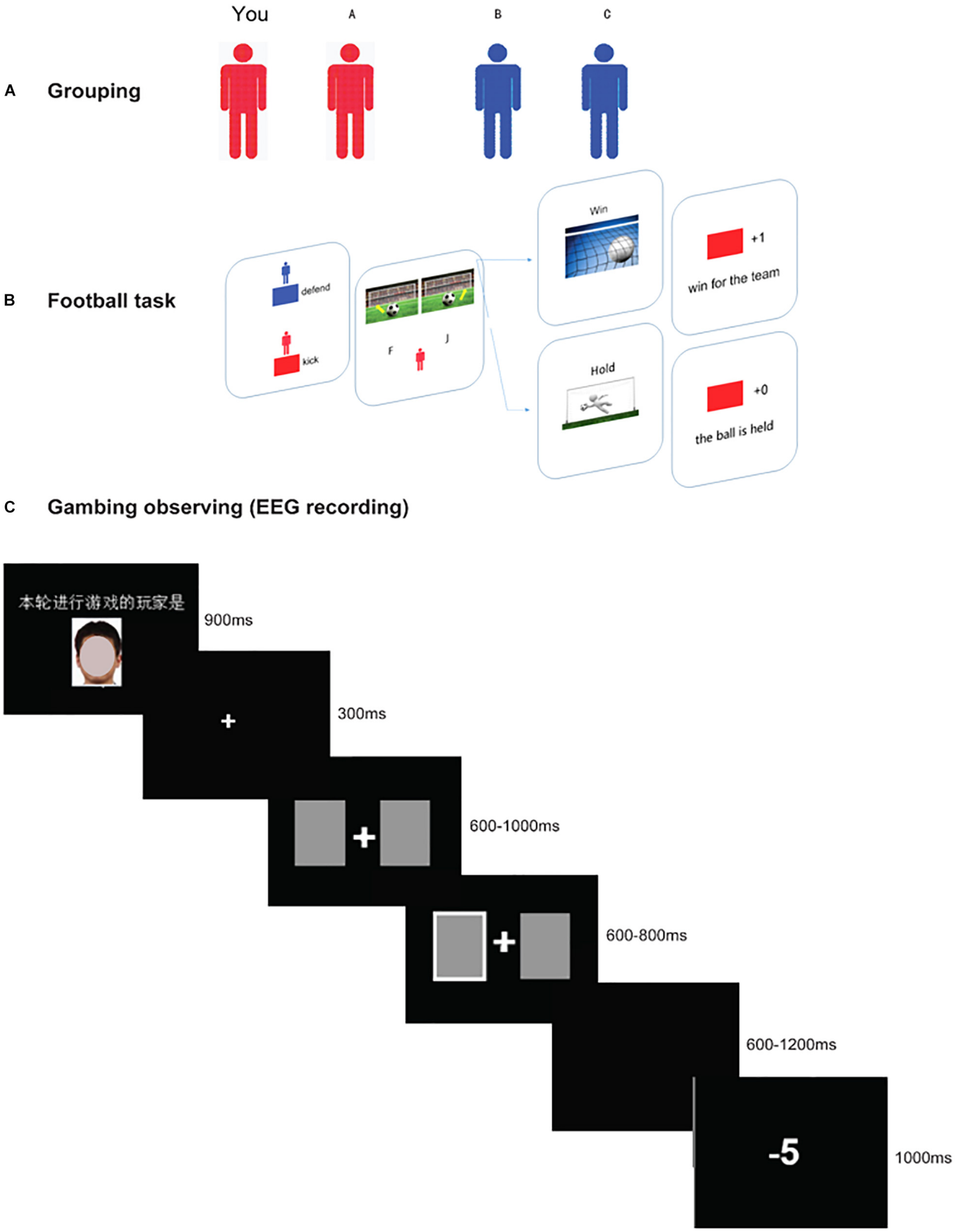

FIGURE 1 | Schematic diagram of the three stages in the present experiment. Panel **(A)** shows the grouping phase, in which participants were randomly arranged in two subgroups (blue team or red team). During this stage, they need to recognize their partner and opponent correctly. Panel **(B)** shows the perspective-taking interactive game. First, the two face a stimulus indicating which two players' turns it is in this trial. The kicking player, who is presented with a ball in front of a goal, has the option to kick the ball to the left or right. At the same time, the defending player (goalkeeper), also needs to select a side by pressing a button ("F" for the left, "J" for the right). If the goalkeeper saves in the same direction as the kicker's direction, the defending team wins; otherwise, the kicking team wins. Thus, in this game, the participants need to enter the opponent's head and choose the opposite direction. The example shows a "win" outcome for the red team. Panel **(C)** shows a two-player gambling task (partner vs. participant) with the time-course of visual stimuli. First, there is a face stimulus (which has been masked to protect the privacy of the participant) indicating which player's turn it is, followed by two cards (600–1000 ms), and the player is asked to choose either of the cards. The chosen card is indicated (600–800 ms), and a win/loss outcome (1000 ms) is presented after a jitter (600–1200 ms). The example shows a "loss" outcome. In this stage, the players who are not selected to play (e.g., the participant) are asked to observe the other's performance.

detected at nine fronto-central electrodes (FP1, FPz, FP2, F1, Fz, F2, FC1, FCz, and FC2) and P300 was detected at nine centro-parietal electrodes (C1, Cz, C2, P1, Pz, P2, CP1, CPz, and CP2). Because we are not interested in the electrode effect in the current study, we pooled the nine electrodes and computed the averaged FRN and P300 amplitudes. The FRN amplitude was measured for each participant as the mean amplitude within the 230–280 ms window, while the P300 was identified as the mean amplitude within the 300–450 ms window. Because we are not interested in the electrode effect in the current study, the averaged FRN and P300 amplitudes were entered into a 2 (feedback valence: win and loss) × 2 (agent: partner and opponent) repeated-measures analysis of variance (ANOVA).

Temporospatial PCA

It is possible that components overlapping in our grand-averaged waveforms, especially for FRN (see **Figure 2**) and the PCA, is a useful tool for the decomposition of ERPs (Foti et al., 2011). Therefore, we also applied temporo-spatial PCA to more clearly identify the FRN and P300 components. PCA Toolkit (EP Toolkit, version 2.23) and MATLAB 7.8 (MathWorks, Natick, MA, United States) were employed to conduct the PCA in this study (Dien, 2010). We first imported the averaged ERPs from the four conditions for each subject to the toolbox. After checking the data for all conditions, a two-step PCA procedure was performed as in the previous study (Zhang et al., 2013), that is, a temporal PCA was performed on all-time points from each participant's average ERPs, with promax rotation. After capturing the variances in the time domain, a spatial PCA was conducted for each of the resultant temporal factors using all of the recording electrodes with an infomax rotation. Finally, three temporal factors × three spatial factors were extracted from our ERP data based on the screen plot, yielding nine temporospatial factor combinations. For our specific interest in FRN and P300, we identified these two components and extracted the amplitudes, which were also put into a 2 (feedback valence: win and loss) × 2 (agent: partner and opponent) repeated-measures ANOVA. All ANOVAs in the current study were with Tukey *post hoc* testing at a significance level of 0.05. The significant *p*-value was set as 0.05, and the effect size was calculated using partial eta squared.

RESULTS

Behavioral and Psychological Data

The mean IRI score was 69 ± 8.30 (SD) and the IOS score was 4.47 ± 1.26. There was no significant difference between the performance rating for the partner (3.53 ± 1.02) and opponent (3.63 ± 0.76) in the football task, t (18) = −0.35, p = 0.73. The performance rating of the gambling task between the partner (3.73 ± 0.93) and opponent (3.42 ± 0.69) was also not significantly different, t (18) = 1.37, p = 0.19.

As an important validation index of the grouping manipulation, the self-reported involvement or seriousness score was 4.05 ± 0.91, showing a relatively high involvement in the observation task. Regarding the football task, 47.3% of the participants (9 participants) were defeated in this game with their teammate and 52.7% won (10 participants), as the random manipulation regulated. Because the winning was equal for the "partner" and "opponent" in the gambling task, 42.1% of the participants (8 participants) chose the opponent and 57.9% chose the partner in the "who wins more" question after the observation task, and the difference of choice probability was not significant. The 2 (outcome valence) × 2 (agent: partner vs. opponent) ANOVA on the happiness rating showed a significant outcome × agent interaction effect, F (1, 18) = 41.53, p = 0.001, $\eta_p{}^2 = 0.698$). The *post hoc* analysis showed an in-group bias and a schadenfreude effect that the happiness rating was significantly higher when the partner win (5.21 ± 0.15) than when he loses (2.68 ± 0.27), as well as when the opponent loses (4.74 ± 0.30) rather than opponent win (3 ± 0.24), ps = 0.01.

Grand-Averaged ERP Results

FRN Component

The repeated-measures 2 (outcome valence) × 2 (agent: partner vs. opponent) ANOVA showed a significant interaction outcome × agent effect, F (1, 18) = 12.73, p = 0.02, $\eta_p{}^2 = 0.415$). Further analysis indicated that the FRN was more negative-going following the opponent's losses (1.85 ± 0.66 μV) than following the partner's losses (3.24 ± 0.65 μV), F (1, 18) = 8.01, p = 0.01. We did not find significant FRN results between opponent's wins (2.63 ± 0.42 μV) and partner's wins (2.63 ± 0.42 μV).

P300 Component

The repeated-measures 2 (outcome valence) × 2 (agent: partner vs. opponent) ANOVA on the P3 amplitude also showed a significant outcome × agent interaction effect, F (1, 18) = 5.51, p = 0.031, $\eta_p{}^2 = 0.245$). Further analysis indicated a smaller P300 for the opponent's losses (5.25 ± 0.81 μV) than for the partner's losses (6.24 ± 0.89 μV), F (1, 18) = 4.86, p = 0.03. The *post hoc* analysis also indicated a significant difference for the opponent's win (6.53 ± 1.01 μV) versus opponent's loss, F (1, 18) = 4.89, p = 0.041, while such a win vs. loss difference was not significant for the partner, p = 0.67.

PCA ERP Results

Nine-factor combinations consisted of three temporal factors and three spatial factors (see **Supplementary Table 1**). We identified the FRN (peaked at Fz on 266 ms) and P300 (peaked at P1 on 378 ms) based on the visual inspection of the factor combinations and the previous PCA results (Foti et al., 2011; Zhang et al., 2013) (see **Figure 3**). These two PCA components were statistically analyzed as the mean amplitudes within different time windows (250–300 ms for PCA-FRN, 300–450 ms for PCA-P300) at their peak channels (i.e., Fz and P1). Thereafter, the mean values of the amplitudes were separately subjected to repeated-measures 2 (outcome valence) × 2 (agent: partner vs. opponent) ANOVAs.

As **Figure 3** shows, we found a PCA-FRN component that was prominent in the fronto-central brain area. However, the outcome × agent ANOVA on the PCA-FRN amplitude failed to find a significant main effect or interaction effect, Fs < 2.50, ps > 0.13.

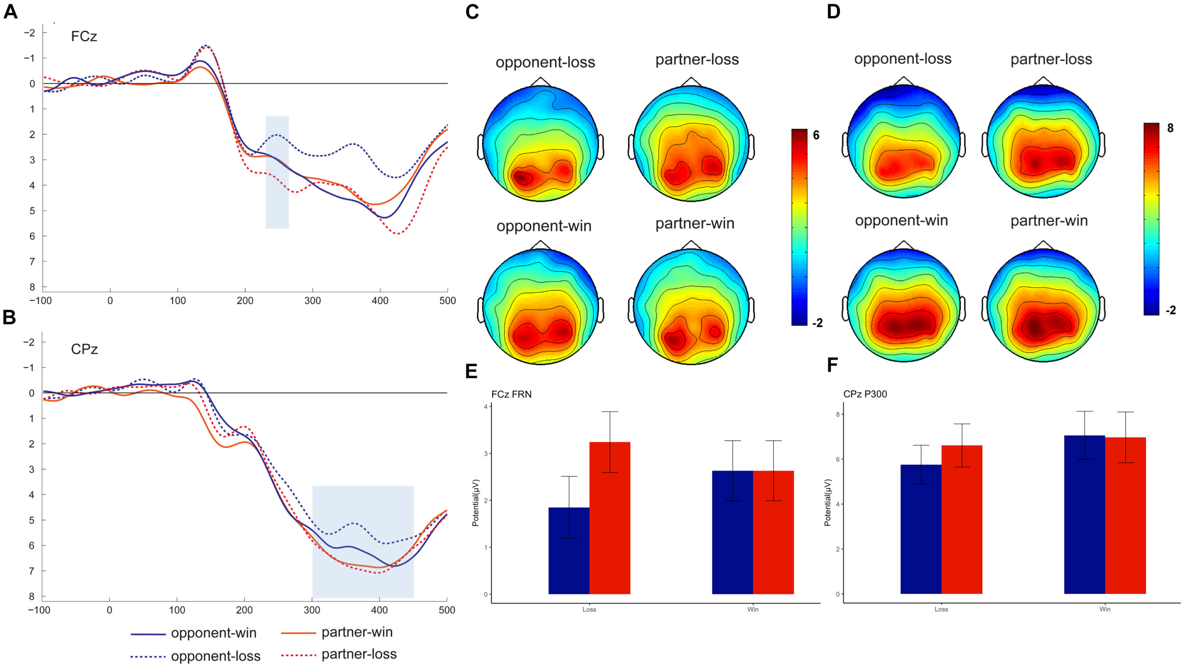

FIGURE 2 | Grand-averaged event-related brain potentials (ERPs). ERPs time-locked to the outcome stimuli at FCz (**A**, mean: **E**) and CPz (**B**, mean: **F**), with the topographical maps for FRN **(C)** and P300 **(D)**.

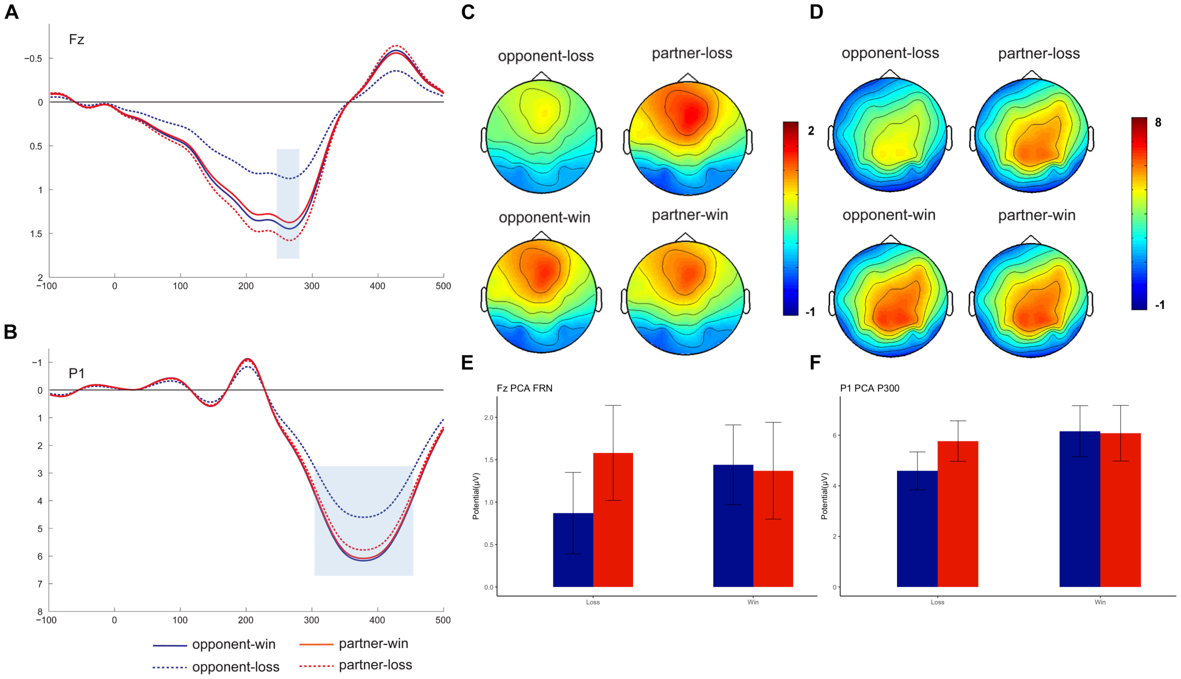

FIGURE 3 | Grand-averaged PCA-FRN and PCA-P300. PCA-FRN components on the peak channel of Fz (**A**, mean: **E**) and PCA-P300 component on the peak channel of P1 (**B**, mean: **F**), with a topographical map showing the fronto-centro FRN **(C)** and centro-parietal P300 **(D)**.

For the PCA-P300 component, the outcome × agent ANOVA showed a nearly significant main effect of the outcome, F (1, 18) = 3.39, p = 0.08, $\eta_p{}^2$ = 0.158. Moreover, there was a significant outcome × agent interaction effect [F (1, 18) = 7.34, p = 0.014, $\eta_p{}^2$ = 0.290], confirming the smaller PCA-P300 for the opponent's losses (4.59 ± 0.75 μV) was relative to following the partner's losses (5.77 ± 0.80 μV), F (1, 18) = 6.85, p = 0.017. Additionally, there was only a significant PCA-P300 win vs. loss difference for the opponent, F (1, 18) = 6.72, p = 0.018.

To confirm the component identification, the correlations between the PCA components and the grand-average components were computed. The correlation analysis showed a significant correlation between FRN and PCA-FRN, with a Pearson correlation of 0.826, p = 0.01. Similarly, the P300 amplitude and PCA-P300 amplitude are also very significant (Pearson correlation r = 0.954), p = 0.01, which confirmed our PCA component analysis.

Correlation Between Questionnaire Data and ERP Results

A previous study showed the association between the IOS scale and the oFRN component (Kang et al., 2010) and the relationship between oMFN and IRI scores (Fukushima and Hiraki, 2009). Therefore, we performed a correlation between the questionnaire (IRI and IOS) scores and the ERP amplitudes (i.e., FRN, P300, PCA-FRN, and PCA-P300). Interestingly, we also found a significant correlation between the IOS score and FRN component (see **Figure 4A**, r = 0.565), p = 0.012, and the correlation between the IOS score and the PCA-FRN component (see **Figure 4B**, r = 0.640) was also significant, p = 0.01. These correlation results indicate that participants' perspective taking increases as the self-other overlap increases. However, no correlation was found for the IRI scores or P300, and there was also no significant correlation between the win/loss or performance rating and the ERP components.

DISCUSSION

We examined the group membership effects on the outcome evaluation. The observation of the others' win or loss can be used as a window to investigate the reaction to the in-group or out-group members' performance. The behavioral rating on the football task and gambling showed no "in-group favoritism." For example, the participants showed no partner vs. opponent performance difference in either task. Considering that the probability of win/loss was made random in the football task and equal in the gambling task, equal performance for the players is reasonable, and it ruled out potential confounding influences of the differential win/loss probability. However, the happiness rating after the experiment showed an in-group bias and schadenfreude effect that the happiness rating was significantly higher when the partner won or the opponent lost. Such an effect confirms the group membership manipulation was successful. Nevertheless, the rating could also be attributed to the expected effect or the "participant demand characteristics" (Nichols and Maner, 2008), that participants may think the experimenter expected them to show an in-group preference in the rating.

For the EEG results, our results first showed the same increase pattern of FRN-P300 components in outcome processing while observing the performances of the non-self agents (the component becomes more negative at opponent loss condition). These two components were further confirmed by the PCA analysis which is consistent with the findings of the previous study (Zhou et al., 2010). Moreover, the ERP data suggested that the amplitude of the FRN and P300 reflected the interaction between the outcome and agent. Interestingly, a prominent win vs. loss differentiation FRN effect was observed on the opponent, i.e., the loss feedback evoked a more negative deflection than win feedback. The win vs. loss differentiation effect of the FRN was consistent with many previous studies' (Miltner et al., 1997; Holroyd and Coles, 2002; Hajcak et al., 2005; Wei et al., 2015; Zheng et al., 2017), but we have not found this win vs. loss differentiation effect on partner's outcomes. Our FRN results seem to reflect the influences of social factors in this early stage of outcome evaluation, which was consistent with the previous study (Qi et al., 2018). However, further PCA-FRN failed to replicate this effect for non-significant interaction effects. One possibility is that the PCA factor is not large enough to reach a significant differentiation effect, even it shows a similar opponent's win vs. opponent's loss difference pattern (**Figure 3A**) as the ERP results (**Figure 2A**). Another possibility is that the early FRN is not sensitive to social relationships, as it may be

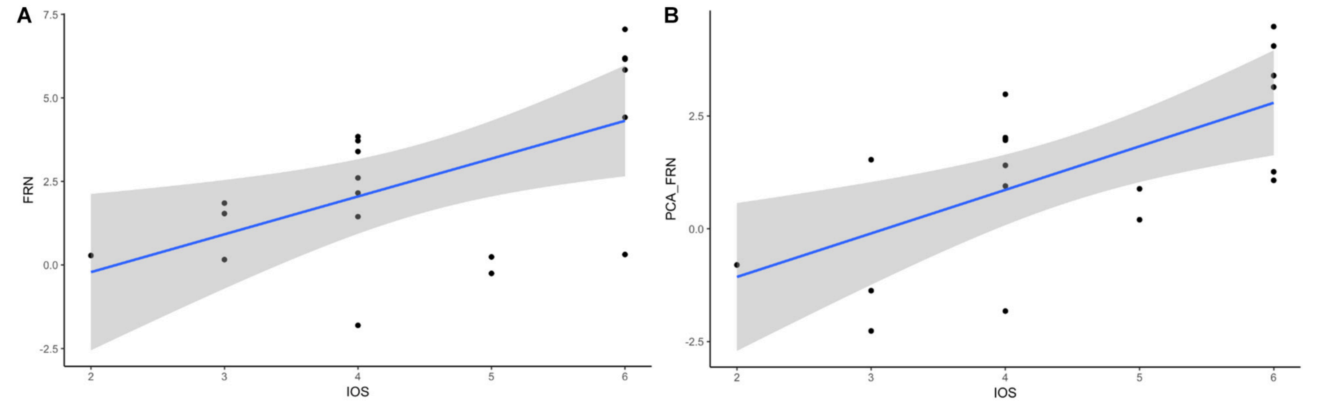

FIGURE 4 | Relationship of FRN-IOS and PCA_FRN-IOS. **(A)** FRN-IOS correlation. **(B)** PCA_FRN-IOS correlation.

entangled with the P300 effect, which is consistent with a previous study showing an interpersonal effect on P300 but not on FRN (Leng and Zhou, 2010).

Likewise, the P300 component showed a similar win vs. loss differentiation effect on the opponent's feedback, but not for the partners. Specifically, the opponent's feedback P300 was more positive for the win trials than for the loss trials. Although whether the feedback P300 is sensitive to the outcome valence is still controversial (Yeung and Sanfey, 2004; Gu et al., 2011), we could infer that there is more "empathy" or concern about the opponent's feedbacks, as it would be consistent with other studies showing a win vs. loss P300 effect on the self's and other's feedback (Wu and Zhou, 2009; Leng and Zhou, 2010). The PCA-P300 results confirmed such greater concern about the opponent's win and loss as the differentiation between win vs. loss. Thereafter, we also observed a partner vs. opponent differential effect in the loss context, showing a smaller P300 and PCA-P300 for the opponent's losses than for the partner's losses. Such an effect, we believe, is attributed to the pronounced opponent loss P300 effect. Unlike Leng and Zhou's (2010) study which showed that P300 was independently modulated by an interpersonal relationship and outcome valence, our results showed the modulation effect of the interaction. The comparison of our ERP results with previous studies in an observation situation (Fukushima and Hiraki, 2006, 2009; Leng and Zhou, 2010; Wang Y. et al., 2014) found FRN and P300 in negative feedback trials became more negative compared to positive feedback trials, for the opponent only. Thus, we can conclude that the participants showed more empathy (perspective-taking) or concern for the opponent's outcome, which manifested a win vs. loss ERP differentiation effect.

As mentioned, a growing number of studies have suggested that outcome evaluation/empathy ERPs are influenced by the relationship between the agent and the observer (Itagaki and Katayama, 2008; Marco-Pallares et al., 2010; Leng and Zhou, 2010; Qi et al., 2018). In general, an experiment designed with close others or others with a higher self-resemblance will cause participants' larger FRN or P3 (Fukushima and Hiraki, 2009; Leng and Zhou, 2010). Together with previous evidence showing more empathy to in-group members (Xu et al., 2009; Contreras-Huerta et al., 2013), the ERP results showed no win vs. loss differentiation effect on the in-group partner, which seemed to be particularly surprising at first sight. The gender of the participants and the group manipulation may account for the partner's indifferent attitude. Because winning or losing did not change the participants' bonuses, the in-group control may not be as effective as out-group control. As several studies suggested, man subjects have a lesser empathetic response than women (Fukushima and Hiraki, 2006; Tousignant et al., 2017). More importantly, recent work showed that women's ERP response of outcome processing was influenced by a short-term induced affective preference, but not that of men (Wang Y. et al., 2014). Furthermore, previous brain imaging studies showing an in-group bias are mainly based on racial or relative long-term social identity (Xu et al., 2009; Contreras-Huerta et al., 2013; Fabi and Leuthold, 2018; Han, 2018). According to male-warrior hypothesis that males respond much stronger sense of competition and are more aggressive in social context (Björkqvist et al., 1994; White and Kowalski, 1994; Van Vugt et al., 2007; Van Vugt, 2009), the man-only participant population may lead to differentiation to opponent's results. Considering that the group identity manipulation in the current study was short-term and temporary, it is interpretable that the men would show very less concern about their partner's performance when the outcome was not related to their own self-interest, but about the opponent's as the potential competition.

However, the brain potential responses showed win vs. loss differential effects on the opponent, which seems like an empathy effect. We noted that one previous ERP study showed both empathy and schadenfreude effects (Itagaki and Katayama, 2008). In Itagaki and Katayama's study, the other's loss elicited FRN (loss-win) under cooperative conditions (i.e., empathy), while the observation of the gain of player A also elicited an FRN in player B under antagonistic conditions (i.e., schadenfreude). Unlike their research, the observation task in our study was neither cooperative nor antagonistic, for the agent's outcome was irrelevant to self-benefit. Therefore, the observer was in a neutral position while viewing the partner's and opponent's performances, which was confirmed by the performance rating for the two agents. Thus, we did not find a schadenfreude effect that the opponent's win evoked a more negative FRN.

By contrast, we found an empathy-like pattern on the opponent's outcomes, that the opponent's loss evoked a more negative FRN and P300. We inferred that the perspective-taking strategic game leads to such an effect. Since the participants have social interaction with the opponent but not partners in the game understanding the opponent's mind is critical for winning the game. Previous work has shown the effect of perspective-taking on decreasing racial bias (Todd et al., 2011; Bimper, 2015; Todd and Simpson, 2016; Müller and Scherr, 2017) and stereotypic bias (Galinsky and Moskowitz, 2000; Wang et al., 2018; Mishra et al., 2019) and increasing the willingness for intergroup contact (Wang C.S. et al., 2014). More importantly, the effect of perspective-taking on improvement in intergroup attitudes was mediated by empathy (Vescio et al., 2003). Combined with Lamm's et al. (2014) study showing that perspective-taking increases empathy, we inferred that the interaction in the competition task reinforced an empathic-like ERP pattern toward the opponents. When participants take the perspective of the opponent, there was a greater overlap between the mental representations of the self and the agent (Davis et al., 1996). The higher self-other overlap results in empathy toward the opponent, which is also confirmed by the correlation between the IOS scores and the FRN component. Therefore, our results provided a shred of evidence for the self-other overlap framework that proposes perspective-taking induces a self-other overlap and further increases social cooperation and ultimately formation of social bonds (Galinsky et al., 2005).

Another interpretation of the win vs. loss differentiation to opponents' performance is that the motivation significance is relatively higher for participants. That is, existing studies have shown FRN was modulated by motivation level. For instance, the FRN was smaller when they observe the others' performance than FRN in joint action (Loehr and Vesper, 2015; Michel et al., 2018). In our study, to some extent, the competitive task has reinforced the motivation to observe the opponents' outcomes due to the interactive game against opponents. Additionally, all the participants in the current study are men, who have higher competitiveness and win orientation in the sports domain (Gill, 1988; Gill et al., 1996), this competitive attitude may increase the motivation to monitor the opponent's performance. A recent study has also confirmed that people showed larger FRN in competitive instruction than in cooperative instruction (Cui et al., 2016).

We admit that the small sample size and the lack of a control group may limit generalization of the conclusion (Christley, 2010)[1]. It would also be very interesting to determine the woman's empathetic response under grouping and perspective-taking manipulation. In the present study, our subjects only included man subjects for several reasons. First, existing studies showed a gender difference in empathy (e.g., women showed more empathetic responses to others) (Han et al., 2008; Lim et al., 2018; Yue et al., 2018) and schadenfreude (e.g., men exhibit more schadenfreude toward others) (Singer et al., 2006). Furthermore, the hormones oxytocin (Shamay-Tsoory et al., 2009; Tetsu et al., 2015) and testosterone (Christian and Shariff, 2017) are associated with schadenfreude or empathy, which also modulate the mentalizing network (Wu et al., 2018). Therefore, we only examined the two effects in man subjects to exclude confounding gender or hormonal factors and investigated the FRN-P300 effect of empathy. Future work that would extend these issues to other situations can provide further evidence about the interaction effect between perspective-taking and group identity on empathy. However, the higher perspective-taking opponent and temporary in-group partner manipulation in the current study only exhibited an empathy pattern to the opponent's outcome. Although the effect of PCA-FRN is not significant, such an effect of the more negative FRN and P300 in response to an opponent's loss versus an opponent's win was observed in the ERP results and PCA-P300. We also look forward to combining perspective-taking, EEG, source localization and connectivity in the future study (Liu et al., 2019) to further investigate this research question.

In summary, our results find neither an in-group bias in empathy nor an intergroup schadenfreude pattern as predicted by the in-group-favoritism hypothesis. Instead, the results of empathy toward the opponent's outcome are consistent with the perspective-taking and self-other overlap hypotheses. Our results also provide a positive view of improving intergroup relationships and forming social bonds by perspective-taking or social interaction.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Institutional Review Boards (IRB) of the Institute of Psychology, Chinese Academy of Sciences. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

HY: whole experiment execution manuscript drafting and part of the statistical analysis. WN and GY: part of the statistical analysis and refine manuscript. QL: refine manuscript and discussion result. HW and XL: supervise whole experiment design, discussion result, and suggestions for organize manuscript draft.

FUNDING

We gratefully acknowledge supports by the National Natural Science Foundation of China (31400963) to HW.

ACKNOWLEDGMENTS

We thank Dr. Kai Wang, Ya Zheng, and Moqian Tian for their roles as confederates in our task. Experimental data of this study can be requested via email to HW, wuhy@psych.ac.cn.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fnins.2019.01162/full#supplementary-material

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[1] Using G*Power (Faul et al., 2007), we calculated that with a sample size of 19, with the current 2 × 2 design, we had a power of $\beta = 0.80$ to detect a very large effect, namely effects that are larger than $p\eta^2 = 0.34/f.72$. For a large sized effect ($p\eta^2 = 0.14/f.40$) the current study had a power of $\beta = 0.35$, and for a medium sized effect ($p\eta^2 = 0.06/f.25$) a power of $\beta = 0.17$. Hence we have to admit that the small sample size severely limited the generalization of the conclusions.

REFERENCES

Bimper, A. (2015). Mentorship of black student-athletes at a predominately white american university: critical race theory perspective on student-athlete development. *Sport Educ. Soc.* 22, 175–193.

Björkqvist, K., Österman, K., and Lagerspetz, K. M. J. (1994). Sex differences in covert aggression among adults. *Aggress. Behav.* 20, 27–33. doi: 10.1002/1098-2337(1994)20:1<27::AID-AB2480200105>3.0.CO;2-Q

Böhm, R., Rusch, H., and Baron, J. (2018). The psychology of intergroup conflict: a review of theories and measures. *J. Econ. Behav. Organ.* doi: 10.1016/j.jebo.2018.01.020

Brewer, M. B. (1979). In-group bias in the minimal intergroup situation: a cognitive-motivational analysis. *Psychol. Bull.* 86, 307–324.

Cao, J., Gu, R., Bi, X., Zhu, X., and Wu, H. (2015). Unexpected acceptance? Patients with social anxiety disorder manifest their social expectancy in ERPs during social feedback processing. *Front. Psychol.* 6:1745. doi: 10.3389/fpsyg.2015.01745

Christian, C. B., and Shariff, A. F. (2017). Asymmetry and empathy: higher asymmetry is associated with lower levels of mentalizing. *Early Hum. Dev.* 111, 6–15. doi: 10.1016/j.earlhumdev.2017.05.004

Christley, R. M. (2010). Power and error: increased risk of false positive results in underpowered studies. *Open Epidemiol. J.* 3, 16–19.

Cikara, M., Botvinick, M. M., and Fiske, S. T. (2011). Us versus them: social identity shapes neural responses to intergroup competition and harm. *Psychol. Sci.* 22, 306–313. doi: 10.1177/0956797610397667

Cikara, M., Bruneau, E., Van Bavel, J. J., and Saxe, R. (2014). Their pain gives us pleasure: how intergroup dynamics shape empathic failures and counter-empathic responses. *J. Exp. Soc. Psychol.* 55, 110–125. doi: 10.1016/j.jesp.2014.06.007

Cohen, T. R., and Insko, C. A. (2008). War and peace possible approaches to reducing intergroup conflict. *Perspect. Psychol. Sci.* 3, 87–93. doi: 10.1111/j.1745-6916.2008.00066.x

Contreras-Huerta, L. S., Baker, K. S., Reynolds, K. J., Batalha, L., and Cunnington, R. (2013). Racial bias in neural empathic responses to pain. *PLoS One* 8:e84001. doi: 10.1371/journal.pone.0084001

Cui, F., Zhu, X., Duan, F., and Luo, Y. (2016). Instructions of cooperation and competition influence the neural responses to others' pain: an erp study. *Soc. Neurosci.* 11, 289–296. doi: 10.1080/17470919.2015.1078258

Dasborough, M., and Harvey, P. (2017). Schadenfreude: the (not so) secret joy of another's misfortune. *J. Bus. Ethics* 141, 1–15.

Davis, M. H., Conklin, L., Smith, A., and Luce, C. (1996). Effect of perspective taking on the cognitive representation of persons: a merging of self and other. *J. Pers. Soc. Psychol.* 70, 713–726. doi: 10.1037/0022-3514.70.4.713

Dickinson, D. L., Masclet, D., and Peterle, E. (2018). Discrimination as favoritism: the private benefits and social costs of in-group favoritism in an experimental labor market. *Eur. Econ. Rev.* 104, 220–236.

Dien, J. (2010). The ERP PCA toolkit: an open source program for advanced statistical analysis of event-related potential data. *J. Neurosci. Methods* 187, 138–145. doi: 10.1016/j.jneumeth.2009.12.009

Dunning, J. P., and Hajcak, G. (2007). Error-related negativities elicited by monetary loss and cues that predict loss. *NeuroReport* 18, 1875–1878.

Fabi, S., and Leuthold, H. (2018). Racial bias in empathy: do we process dark- and fair-colored hands in pain differently? an eeg study. *Neuropsychologia* 114, 143–157. doi: 10.1016/j.neuropsychologia.2018.04.024

Faul, F., Erdfelder, E., Lang, A. G., and Buchner, A. (2007). G*power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behav. Res. Methods* 39, 175–191.

Foti, D., Weinberg, A., Dien, J., and Hajcak, G. (2011). Event-related potential activity in the basal ganglia differentiates rewards from nonrewards: response to commentary. *Hum. Brain Mapp.* 32, 2267–2269. doi: 10.1002/hbm.21357

Fukushima, H., and Hiraki, K. (2006). Perceiving an opponent's loss: gender-related differences in the medial-frontal negativity. *Soc. Cogn. Affect. Neurosci.* 1, 149–157. doi: 10.1093/scan/nsl020

Fukushima, H., and Hiraki, K. (2009). Whose loss is it? Human electrophysiological correlates of non-self reward processing. *Soc. Neurosci.* 4, 261–275. doi: 10.1080/17470910802625009

Galinsky, A. D., Ku, G., and Wang, C. S. (2005). Perspective-taking and self-other overlap: fostering social bonds and facilitating social coordination. *Group Process. Intergroup Relat.* 8, 109–124.

Galinsky, A. D., Maddux, W. W., Gilin, D., and White, J. B. (2008). Why it pays to get inside the head of your opponent - The differential effects of perspective taking and empathy in negotiations. *Psychol. Sci.* 19, 378–384. doi: 10.1111/j.1467-9280.2008.02096.x

Galinsky, A. D., and Moskowitz, G. B. (2000). Perspective-taking: decreasing stereotype expression, stereotype accessibility, and in-group favoritism. *J. Pers. Soc. Psychol.* 78, 708–724. doi: 10.1037//0022-3514.78.4.708

Gill, D. L. (1988). Gender differences in competitive orientation and sport participation. *Int. J. Sport Psychol.* 19, 145–159.

Gill, D. L., Williams, L., Dowd, D. A., Beaudoin, C. M., and Martin, J. J. (1996). Competitive orientations and motives of adult sport and exercise participants. *J. Sport Behav.* 19, 307–318.

Gu, R., Lei, Z., Broster, L., Wu, T., Jiang, Y., and Luo, Y. (2011). Beyond valence and magnitude: a flexible evaluative coding system in the brain. *Neuropsychologia* 49, 3891–3897. doi: 10.1016/j.neuropsychologia.2011.10.006

Han, S., Fan, Y., and Mao, L. (2008). Gender difference in empathy for pain: an electrophysiological investigation. *Brain Res.* 1196, 85–93. doi: 10.1016/j.brainres.2007.12.062

Hajcak, G., Holroyd, C. B., Moser, J. S., and Simons, R. F. (2005). Brain potentials associated with expected and unexpected good and bad outcomes. *Psychophysiology* 42, 161–170. doi: 10.1111/j.1469-8986.2005.00278.x

Hajcak, G., Moser, J. S., Holroyd, C. B., and Simons, R. F. (2006). The feedback-related negativity reflects the binary evaluation of good versus bad outcomes. *Biol. Psychol.* 71, 148–154.

Han, S. (2018). Neurocognitive basis of racial ingroup bias in empathy. *Trends Cogn. Sci.* 22, 400–421. doi: 10.1016/j.tics.2018.02.013

Hein, G., Silani, G., Preuschoff, K., Batson, C. D., and Singer, T. (2010). Neural responses to ingroup and outgroup members' suffering predict individual differences in costly helping. *Neuron* 68, 149–160. doi: 10.1016/j.neuron.2010.09.003

Holroyd, C. B., Baker, T. E., Kerns, K. A., and Ulrich, M. (2008). Electrophysiological evidence of atypical motivation and reward processing in children with attention-deficit hyperactivity disorder. *Neuropsychologia* 46, 2234–2242. doi: 10.1016/j.neuropsychologia.2008.02.011

Holroyd, C. B., and Coles, M. G. H. (2002). The neural basis of human error processing: reinforcement learning, dopamine, and the error-related negativity. *Psychol. Rev.* 109, 679–709. doi: 10.1037/0033-295X.109.4.679

Itagaki, S., and Katayama, J. (2008). Self-relevant criteria determine the evaluation of outcomes induced by others. *Neuroreport* 19, 383–387. doi: 10.1097/WNR.0b013e3282f556e8

Kang, S. K., Hirsh, J. B., and Chasteen, A. L. (2010). Your mistakes are mine: self-other overlap predicts neural response to observed errors. *J. Exp. Soc. Psychol.* 46, 229–232. doi: 10.1016/j.jesp.2009.09.012

Lamm, C., Batson, C. D., and Decety, J. (2014). The neural substrate of human empathy: effects of perspective-taking and cognitive appraisal. *J. Cogn. Neurosci.* 19, 42–58.

Leng, Y., and Zhou, X. (2010). Modulation of the brain activity in outcome evaluation by interpersonal relationship: an ERP study. *Neuropsychologia* 48, 448–455. doi: 10.1016/j.neuropsychologia.2009.10.002

Lim, J. A., Choi, S. H., Lee, W. J., Jang, J. H., and Kang, D. H. (2018). Cognitive-behavioral therapy for patients with chronic pain: implications of gender differences in empathy. *Medicine* 97:e10867. doi: 10.1097/MD.0000000000010867

Liu, Q., Wu, H., Doyle, J., Wilson, A., Corlier, J., and Leuchter, A. (2019). 10 Hz rTMS-induced neural response of gamma oscillations in subgenual anterior cingulate cortex (sgACC) is anti-correlated with left dorsolateral prefrontal cortex (DLPFC) in major depressive disorder. *Brain Stimul. Basic Transl. Clin. Res. Neuromodul.* 12:544.

Loehr, J., and Vesper, C. (2015). The sound of you and me: novices represent shared goals in joint action. *Quart. J. Exp. Psychol.* 69, 536–547. doi: 10.1080/17470218.2015.1061029

Luo, Y., Wu, T., Broster, L. S., Feng, C., Zhang, D., Gu, R., et al. (2014). The temporal course of the influence of anxiety on fairness considerations. *Psychophysiology* 51, 834–842. doi: 10.1111/psyp.12235

Marco-Pallares, J., Kramer, U. M., Strehl, S., Schroder, A., and Munte, T. F. (2010). When decisions of others matter to me: an electrophysiological analysis. *BMC Neurosci.* 11:86. doi: 10.1186/1471-2202-11-86

Mathur, V. A., Harada, T., Lipke, T., and Chiao, J. Y. (2010). Neural basis of extraordinary empathy and altruistic motivation. *NeuroImage* 51, 1468–1475. doi: 10.1016/j.neuroimage.2010.03.025

Mcdonald, M., Brindley, S., Halperin, E., and Saguy, T. (2017). Outgroup members' internal criticism promotes intergroup openness: the role of perceived risk. *Br. J. Soc. Psychol.* 57, 95–111.

Michel, R., Jens, B., and Roman, L. (2018). When a social experimenter overwrites effects of salient objects in an individual go/no-go simon task – an erp study. *Front. Psychol.* 9:674. doi: 10.3389/fpsyg.2018.00674

Miltner, W. H. R., Braun, C. H., and Coles, M. G. H. (1997). Event-related brain potentials following incorrect feedback in a time-estimation task: evidence for a "generic" neural system for error detection. *J. Cogn. Neurosci.* 9, 788–798. doi: 10.1162/jocn.1997.9.6.788

Miltner, W. H. R., Lemke, U., Weiss, T., Holroyd, C., Scheffers, M. K., and Coles, M. G. H. (2003). Implementation of error-processing in the human anterior cingulate cortex: a source analysis of the magnetic equivalent of the error-related negativity. *Biol. Psychol.* 64, 0–166.

Mishra, A., Mishra, H., and Rathee, S. (2019). Examining the presence of gender bias in customer reviews using word embedding. *SSRN Elect. J.* doi: 10.13140/RG.2.2.15426.02240

Molenberghs, P., Hayward, L., Mattingley, J. B., and Cunnington, R. (2012). Activation patterns during action observation are modulated by context in mirror system areas. *Neuroimage* 59, 608–615. doi: 10.1016/j.neuroimage.2011.07.080

Montalan, B., Lelard, T., Godefroy, O., and Mouras, H. (2012). Behavioral investigation of the influence of social categorization on empathy for pain: a minimal group paradigm study. *Front. Psychol.* 3:389. doi: 10.3389/fpsyg.2012.00389

Morrison, S., Decety, J., and Molenberghs, P. (2012). The neuroscience of group membership. *Neuropsychologia* 50, 2114–2120. doi: 10.1016/j.neuropsychologia.2012.05.014

Müller, P., and Scherr, S. (2017). Reducing the bias: how perspective taking affects first- and third-person perceptions of media influence. *Commun. Res. Rep.* 34, 134–142.

Nichols, A. L., and Maner, J. K. (2008). The good-subject effect: investigating participant demand characteristics. *J. Gen. Psychol.* 135, 151–165. doi: 10.3200/Genp.135.2.151-166

Oestereich, A., Crokidakis, N., and Pires, M. (2019). Three-state opinion dynamics in modular networks. *Phys. Rev. E* 100:032312. doi: 10.1103/PhysRevE.100.032312

Osinsky, R., Ulrich, N., Mussel, P., Feser, L., and Hewig, J. (2016). The feedback-related negativity reflects the combination of instantaneous and long-term values of decision outcomes. *J. Cogn. Neurosci.* 29, 1–11. doi: 10.1162/jocn_a_01055

Preis, M. A., Schmidt-Samoa, C., Dechent, P., and Kroener-Herwig, B. (2013). The effects of prior pain experience on neural correlates of empathy for pain: an fmri study. *Pain* 154, 411–418. doi: 10.1016/j.pain.2012.11.014

Qi, Y., Wu, H., and Liu, X. (2018). Social value orientation modulates context-based social comparison preference in the outcome evaluation: an erp study. *Neuropsychologia* 112, 135–144. doi: 10.1016/j.neuropsychologia.2018.02.028

Shamay-Tsoory, S. G., Fischer, M., Dvash, J., Harari, H., Perach-Bloom, N., and Levkovitz, Y. (2009). Intranasal administration of oxytocin increases envy and schadenfreude (Gloating). *Biol. Psychiatry* 66, 864–870. doi: 10.1016/j.biopsych.2009.06.009

Sherif, M. (1966). *In Common Predicament: Social Psychology of Intergroup Conflict and Cooperation*. Boston, MA: Houghton Mifflin.

Sherif, M., Harvey, O. J., White, B. J., Hood, W. R., and Sherif, C. W. (1961). Intergroup conflict and cooperation: the robbers cave experiment. *Sociol. Forum* 19, 663–666.

Shih, M., Wang, E., Bucher, A. T., and Stotzer, R. (2009). Perspective taking: reducing prejudice towards general out-groups and specific individuals. *Group Process. Intergroup Relat.* 12, 565–577. doi: 10.1177/1368430209337463

Singer, T., Seymour, B., O'Doherty, J. P., Stephan, K. E., Dolan, R. J., and Frith, C. D. (2006). Empathic neural responses are modulated by the perceived fairness of others. *Nature* 439, 466–469. doi: 10.1038/nature04271

Steinbeis, N., and Singer, T. (2014). Projecting my envy onto you: neurocognitive mechanisms of an offline emotional egocentricity bias. *Neuroimage* 102(Pt 2), 370–380. doi: 10.1016/j.neuroimage.2014.08.007

Struch, N., and Schwartz, S. H. (1989). Intergroup aggression: its predictors and distinctness from in-group bias. *J. Pers. Soc. Psychol.* 56, 364–373.

Tajfel, H. (1970). Experiments in intergroup discrimination. *Sci. Am.* 223, 96–102.

Tajfel, H., Billig, M. G., Bundy, R. P., and Flament, C. (1971). Social categorization and intergroup behaviour. *Eur. J. Soc. Psychol.* 1, 149–178. doi: 10.1002/ejsp.2420010202

Talmi, D., Atkinson, R., and El-Deredy, W. (2013). The feedback-related negativity signals salience prediction errors, not reward prediction errors. *J. Neurosci.* 33, 8264–8269. doi: 10.1523/jneurosci.5695-12.2013

Tetsu, H., Mitsuru, K., Eiichi, O., Yuko, Y., Hirotoshi, H., Toshio, M., et al. (2015). Attentional control and interpretation of facial expression after oxytocin administration to typically developed male adults. *PLoS One* 10:e0116918. doi: 10.1371/journal.pone.0116918

Todd, A. R., Bodenhausen, G. V., Richeson, J. A., and Galinsky, A. D. (2011). Perspective taking combats automatic expressions of racial bias. *J. Pers. Soc. Psychol.* 100, 1027–1042. doi: 10.1037/a0022308

Todd, A. R., and Simpson, A. J. (2016). Perspective taking and member-to-group generalization of implicit racial attitudes: the role of target prototypicality. *Eur. J. Soc. Psychol.* 47, 105–112.

Tousignant, B., Eugene, F., and Jackson, P. L. (2017). A developmental perspective on the neural bases of human empathy. *Infant Behav. Dev.* 48(Pt A), 5–12. doi: 10.1016/j.infbeh.2015.11.006

Van Bavel, J. J., Packer, D. J., and Cunningham, W. A. (2008). The neural substrates of in-group bias: a functional magnetic resonance imaging investigation. *Psychol. Sci.* 19, 1131–1139. doi: 10.1111/j.1467-9280.2008.02214.x

Van Vugt, M. (2009). Sex differences in intergroup competition, aggression, and warfare the male warrior hypothesis. *Values Empathy Fairness Across Soc. Barr.* 1167, 124–134. doi: 10.1111/j.1749-6632.2009.04539.x

Van Vugt, M., De Cremer, D., and Janssen, D. P. (2007). Gender differences in cooperation and competition - The male-warrior hypothesis. *Psychol. Sci.* 18, 19–23. doi: 10.1111/j.1467-9280.2007.01842.x

Vescio, T. K., Sechrist, G. B., and Paolucci, M. P. (2003). Perspective taking and prejudice reduction: the mediational role of empathy arousal and situational attributions. *Eur. J. Soc. Psychol.* 33, 455–472. doi: 10.1002/ejsp.163

Vollberg, M. C., and Cikara, M. (2018). The neuroscience of intergroup emotion. *Curr. Opin. Psychol.* 24, 48–52. doi: 10.1016/j.copsyc.2018.05.003

Wang, C. S., Lee, M., Ku, G., and Leung, K. Y. (2018). The cultural boundaries of perspective-taking: when and why perspective-taking reduces stereotyping. *Pers. Soc. Psychol. Bull.* 44, 928–943. doi: 10.1177/0146167218757453

Wang, C. S., Tai, K., Ku, G., and Galinsky, A. D. (2014). Perspective-taking increases willingness to engage in intergroup contact. *PLoS One* 9:e85681. doi: 10.1371/journal.pone.0085681

Wang, Y., Qu, C., Luo, Q., Qu, L., and Li, X. (2014). Like or Dislike? Affective preference modulates neural response to others' gains and losses. *PLoS One* 9:e105694. doi: 10.1371/journal.pone.0105694

Wei, W., Wang, L., Shang, Z., and Li, J. C. (2015). Non-sympathetic frn responses to drops in others' stocks. *Soc. Neurosci.* 10, 1–8. doi: 10.1080/17470919.2015.1013222

White, J. W., and Kowalski, R. M. (1994). Deconstructing the myth of the nonaggressive woman: *a feminist analysis*. *Psychol. Women Q.* 18, 487–508. doi: 10.1111/j.1471-6402.1994.tb01045.x

Wu, H., Feng, C., Lu, X., Liu, X., and Liu, Q. (2018). Oxytocin effects on the resting-state mentalizing brain network. *bioRxiv[Preprint]* doi: 10.1101/465658

Wu, Y., and Zhou, X. (2009). The p300 and reward valence, magnitude, and expectancy in outcome evaluation. *Brain Res.* 1286, 114–122. doi: 10.1016/j.brainres.2009.06.032

Xin, L., Xinmu, H., Kan, S., and Xiaoqin, M. (2018). Empathy modulates the evaluation processing of altruistic outcomes. *Front. Psychol.* 9:407. doi: 10.3389/fpsyg.2018.00407

Xu, X., Zuo, X., Wang, X., and Han, S. (2009). Do you feel my pain? Racial group membership modulates empathic neural responses. *J. Neurosci.* 29, 8525–8529. doi: 10.1523/JNEUROSCI.2418-09.2009

Yang, S., Huang, X., Chen, Y., Fu, Y., and Liu, M. (2014). Effect of interpersonal distance on neural basis of self- and other representation: evidence from the oFRN component. *Acta Psychologica Sinica* 46, 666–676.

Yeung, N., and Sanfey, A. G. (2004). Independent coding of reward magnitude and valence in the human brain. *J. Neurosci.* 24, 6258–6264.

Yue, T., Huang, X., and Liu, G. (2018). The effects of oxytocin on empathic response and its mechanisms. 26, 442–453.

Zhang, D., Gu, R., Wu, T., Broster, L. S., Luo, Y., Jiang, Y., et al. (2013). An electrophysiological index of changes in risk decision-making strategies. *Neuropsychologia* 51, 1397–1407. doi: 10.1016/j.neuropsychologia.2013.04.014

Zhao, Q., Li, H., Hu, B., Wu, H., and Liu, Q. (2017). Abstinent heroin addicts tend to take risks: ERP and source localization. *Front. Neurosci.* 11:681. doi: 10.3389/fnins.2017.00681

Zheng, Y., Li, Q., Zhang, Y., Li, Q., Shen, H., Gao, Q., et al. (2017). Reward processing in gain versus loss context: an erp study. *Psychophysiology* 54, 1040–1053. doi: 10.1111/psyp.12855

Zhou, Z., Yu, R., and Zhou, X. (2010). To do or not to do? Action enlarges the FRN and P300 effects in outcome evaluation. *Neuropsychologia* 48, 3606–3613. doi: 10.1016/j.neuropsychologia.2010.08.010

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers
in Neuroscience

ORIGINAL RESEARCH
published: 10 July 2019
doi: 10.3389/fnins.2019.00724

Reduced Hedonic Valuation of Rewards and Unaffected Cognitive Regulation in Chronic Stress

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Cognition can influence choices by modulation of decision-making processes. This cognitive regulation is defined as processing information, applying knowledge, and changing preferences to consciously modulate decisions. While cognitive regulation of emotions has been extensively studied in psychiatry, few works have detailed cognitive regulation of decision-making. Stress may influence emotional behavior, cognition, and decision-making. In addition, the brain regions responsible for decision-making are sensitive to stress-induced changes. Thus, we hypothesize that chronic stress may disrupt the ability to regulate choices. Herein, we used a functional magnetic resonance imaging task where fourteen control and fifteen chronically stressed students had to cognitively upregulate or downregulate their craving before placing a bid to obtain food. We found that stressed participants placed lower bids to get the reward and chose less frequently higher bid values for food. Nevertheless, we did not find neural and behavioral differences during cognitive regulation of craving. Our outcomes revealed that chronic stress impacts decision-making after cognitive regulation of craving by reducing the valuation of food rewards but not cognitive modulation itself. Importantly, our results need further validation with larger sample sizes.

Keywords: stress, decision-making, cognition, magnetic resonance imaging, fMRI, reward, human, food

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Specialty section:
This article was submitted to
Decision Neuroscience,
a section of the journal
Frontiers in Neuroscience

Received: *15 February 2019*
Accepted: *28 June 2019*
Published: *10 July 2019*

Citation:
Ferreira S, Veiga C, Moreira P, Magalhães R, Coelho A, Marques P, Portugal-Nunes C, Sousa N and Morgado P (2019) Reduced Hedonic Valuation of Rewards and Unaffected Cognitive Regulation in Chronic Stress. Front. Neurosci. 13:724.
doi: 10.3389/fnins.2019.00724

INTRODUCTION

Value-based decision-making is the ability to make a choice from competing courses of action/alternatives based on subjective values and possible outcomes attributed to them (Balleine, 2005). This process is carried out whenever a person chooses from different alternatives (e.g., choosing between eating an apple or an orange, or between going out or not). Different interacting systems are responsible for the valuation and action selection processes in the brain (Rangel et al., 2008). First, a valuation system computes the action values. A comparator system needs to evaluate the action values. An accumulator system receives and accumulates the value signals from the

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Abbreviations: ACTH, adrenocorticotropic hormone; BAI, Beck Anxiety Inventory; BDI, Beck Depression Inventory; dlPFC, dorsolateral prefrontal cortex; fMRI, functional magnetic resonance imaging; GLM, general linear model; MNI, Montreal Neurological Institute; PSS-10, 10-items Perceived Stress Scale; vmPFC, ventromedial prefrontal cortex.

comparator system until the signal for one of the actions is sufficiently strong for the choice to be executed (Gold and Shadlen, 2007; Basten et al., 2010).

Values assigned to actions during the valuation process can be influenced by different factors such as the degree of risk or uncertainty of the action (Platt and Huettel, 2008; Rangel et al., 2008). Humans have a natural aversion to risky or uncertain choices and place less value on actions with temporal uncertain rewards or multiple sets of outcomes (Christopoulos et al., 2009; McGuire and Kable, 2012). Individuals often place higher values on immediate rewards rather than on future ones (Rangel et al., 2008). Social competition, cooperation, and concerns for the well-being of others also influence decision-making (Fehr and Camerer, 2007). Cognition can also influence choices through modulation of the decision-making processes. This cognitive regulation process may be defined as processing information, applying knowledge and changing preferences to consciously modulate our decisions. While cognitive regulation of emotional response has been extensively studied (Ochsner et al., 2004; Delgado et al., 2008; Wager et al., 2008), few works have detailed cognitive regulation of decision-making. A functional magnetic resonance imaging (fMRI) study where participants had to modulate their cravings for food showed that cognitive regulation affects decision-making through valuation regulation and behavioral control (Hutcherson et al., 2012). The ventromedial prefrontal cortex (vmPFC) is known to compute the value signal of decisions while the dorsolateral prefrontal cortex (dlPFC) modulates this signal during cognitive regulation tasks (Hare et al., 2009, 2011; Kober et al., 2010).

Cognitive regulation of both emotion and decision-making has a role in the treatment of several conditions (schizophrenia, bipolar disorder, depression, obesity, addiction, obsessive-compulsive disorder, and eating disorders) where emotional processing and decision-making are often impaired (Phillips et al., 2003; Ochsner et al., 2004). On the other hand, mental disorders such as schizophrenia, bipolar disorder, post-traumatic stress disorder, and depression are often associated with prolonged exposure to stress (Arnsten, 2015; Sousa, 2016). Stress impacts emotional processing leading to depressive and anxious behavior associated with alterations in amygdala-ventromedial-prefrontal pathways. Moreover, stress elicits cognitive impairments namely working memory and attentional deficits, poor decision-making (e.g., decreased reward sensitivity or increased influence of immediate rewards), behavioral inflexibility, and learning deficits. These cognitive differences are associated with changes in prefrontal and hippocampal regions (Sandi, 2013; Arnsten, 2015; Chen and Baram, 2016; Sousa, 2016). Additionally, the brain regions implicated in decision-making processes are sensitive to stress-induced changes. In fact, changes in fronto-striatal networks involved in behavioral decisions have been reported in both humans and rodents after chronic stress (Dias-Ferreira et al., 2009; Soares et al., 2012; Morgado et al., 2012, 2015a; Sousa, 2016; Magalhães et al., 2018). Thus, stress seems to influence the quality of decisions (Starcke and Brand, 2012; Morgado et al., 2015b; Bryce and Floresco, 2016; Chen and Baram, 2016) because cognitive control is diminished (Yu, 2016).

Stress has also an impact on appetite and eating behavior (Ans et al., 2018) and is one of the factors for development of eating and obesity-associated conditions (Razzoli et al., 2017). Usually, the production of adrenocorticotropic hormone (ACTH) by the anterior pituitary gland leads to the release of cortisol in the adrenal cortex to stimulate hunger and feeding behavior. High cortisol levels are associated with high insulin concentrations resulting in increased caloric intake or food craving (Adam and Epel, 2007). Stress might boost these pathways leading to an increase in food intake and appetite for high-caloric food, or also reduced reward sensitivity to low-caloric food (Razzoli et al., 2017; Ans et al., 2018; Berg Schmidt et al., 2018; Ferrer-Cascales et al., 2018), in agreement with previous stress decision-making studies demonstrating decreased reward sensitivity or increased influence of immediate rewards (Morgado et al., 2015b). Thus, stress seems to be associated with increased food reward sensitivity due to diminished self-control during food choice associated with decreased functional connectivity between the vmPFC and dlPFC (Neseliler et al., 2017) and increased connectivity between the vmPFC and subcortical regions (amygdala and striatum) (Tryon et al., 2013; Maier et al., 2015).

Herein, we used an fMRI task to clarify the impact of chronic stress on cognitive regulation of decisions. Our task consisted of cognitively upregulating or downregulating craving before placing a bid to obtain food. In addition to brain responses, we analyzed behavioral parameters (food valuation score and reaction time) associated with the task, and blood hormonal changes after the task (insulin, cortisol, and glucose). Regarding the previous findings, we hypothesize that chronic stress may disrupt the ability of individuals to regulate their choices. We expect that cognitive regulation deficits after chronic stress manifest by changes in the prefrontal cortex (vmPFC and dlPFC). Subsequently, these deficits lead to decision-making impairments, namely increased reward sensitivity, underlying brain response alterations in prefrontal and striatal regions. Moreover, we expect that chronic stress participants present augmented levels of insulin, glucose, and cortisol after the stimulation with food pictures due to an increased reward sensitivity to food.

MATERIALS AND METHODS

Subjects

We enrolled in this study medical students from the School of Medicine of University of Minho, Portugal. All students were healthy Caucasians, right-handed, and had a healthy body-mass index. One group was under normal academic activities [control group, $n = 14$; 9 females/5 males; median (range) 23.00 (3.00) years of age; education 17.00 (3.00) years] and the other included subjects on the long period of preparation for the medical licensing exam [chronic psychosocial stress condition; stress group, $n = 15$; 10 females/5 males; 24.00 (3.00) years of age; education 18.00 (0.00) years]. This work was conducted 1 to 3 months before the exam, but students usually start preparing 1 year before the exam. Subjects were eligible if they were at least

18 years old, reported no history of psychiatric or neurological conditions, traumatic brain lesion, or substance abuse, and were not on any psychiatric medication. The groups were matched for gender (chi-squared test $\chi^2_{(1)} = 0.02$, $p = 0.893$) but not for age (Mann–Whitney test $U = 169.00$, $p = 0.004$, effect size $r = 0.56$) and education level ($U = 210.00$, $p = 2.579 \times 10^{-8}$, $r = 0.93$).

Ethics Statement

The study was performed in accordance with the Declaration of Helsinki and was approved by Ethics Subcommittee for the Life and Health Sciences of University of Minho, Portugal, and by the Ethics Committee of the Hospital of Braga, Portugal. All subjects were provided with written informed consent following description of the study goals and procedures.

Sociodemographic and Psychological Scales

Subjects filled a questionnaire to characterize gender, age, educational level, handedness, and ethnic origin. Weight and height were also measured to prevent the inclusion of participants with an unhealthy body mass index. Subjects were assessed with the 10-items Perceived Stress Scale (PSS-10) (Cohen et al., 1983; Morgado et al., 2013), the Beck Anxiety Inventory (BAI) (Beck et al., 1988), and the Beck Depression Inventory (BDI) (Beck et al., 1996). PSS-10 measures the extent to which participants perceived their life as unpredictable, uncontrollable, and overloaded during the previous month. The higher the score, the greater the intensity of perceived stress. BAI measures the severity of an individual's anxiety during the previous week. Scores lower than 8 indicate minimal anxiety. Scores higher than 7, 15, and 25 indicate mild, moderate, and severe anxiety, respectively. BDI measures the severity of depression and can be used as a screening tool. Scores lower than 14 indicate minimal depression. Higher scores indicate more severe depressive symptoms.

Blood Sampling and Analysis

Before the fMRI acquisition, samples of venous blood were collected from all participants into a 5 mL potassium ethylenediaminetetraacetic acid tube and a serum tube. We repeated the collection immediately after the fMRI acquisition. Pre-scan blood samples were used to measure cortisol, glucose, insulin, and ACTH serum levels. In post-scan samples, we repeated cortisol, glucose, and insulin serum measurements (ACTH measurement was not repeated due to technical constraints). The collection took place between 2 and 7 pm which assures small variation in cortisol levels during this period (Minkley and Kirchner, 2012). ACTH was measured based on solid-phase, two-site sequential chemiluminescent immunometric assay, and insulin with solid-phase, enzyme-labeled chemiluminescent immunometric assay (IMMULITE 2000, Siemens AG, Germany). Cortisol levels were assessed with competitive immunoassay based on direct chemiluminescent (ADVIA Centaur and Centaur XP, Siemens AG, Germany). Glucose was measured based on the hexokinase-glucose-6-phosphate method (Dimension Vista, Siemens AG, Germany). Standard procedures were applied following the manufacturer instructions.

Statistical Analysis

Data related with psychological scales, laboratory values, and behavioral parameters were analyzed using IBM SPSS Statistics (version 24.0; IBM Corporation, United States). Kolmogorov–Smirnov and Shapiro–Wilk tests were used to assess for normality in the distribution of data. Comparisons between groups were carried out by parametric *t*-tests or repeated measures ANOVA (*F*-test, with Bonferroni correction for multiple comparisons for *post hoc* tests], or non-parametric Mann-Whitney *U*-tests. Differences were considered statistically significant if $p < 0.05$. Effect sizes were calculated for all statistically significant results.

fMRI Task

The task was adapted from Hutcherson et al. (2012). Subjects were instructed to fast for at least 4 h before their arrival and to eat a light meal before the fasting period to increase the valuation of food pictures. We also informed that they would remain in the laboratory for 30 min at the end of the experiment to eat the food they obtained during the fMRI task. The task consisted of two parts: a pre-scan rating task that provided us with a measure of the baseline value for food, and an in-scan bidding and regulation task that measured the food value under the influence of regulation.

During the pre-scan rating task, subjects were shown 150 pictures of different snack food items (e.g., cake, chips, and candy) and rated, at their own pace, how much they would like to eat them using a four-point scale (1, "Don't want it at all"; 4, "Want it a lot"). Our set of pictures was adapted to the Portuguese context of food.

Afterward, subjects received instructions for the in-scan bidding and regulation task (**Figure 1**). The 150 snack food pictures were shown again, separated into three trial conditions: indulge, distance, and natural. Each type of trial appeared 50 times, randomly interspersed over the scanning run. On each trial, before the food appeared, participants saw an abstract black-and-white symbol indicating the trial type (cue, 2 s). On indulge trials, subjects were instructed to try to increase their craving for the snack using any strategy they needed to. During distance trials, the instruction consisted on trying to decrease their craving. On natural trials, they had to allow thoughts and feelings to come naturally. Subjects had 4 s to look at the item and engage in the craving cognitive regulation task (hereinafter referred as cognitive regulation task). After the 4 s, subjects had 2 s to place a bid (0 €, 1 €, 2 €, or 3 €) for the right to eat that food at the end of the experiment. They were asked to treat each trial as if it were the only decision that counted. These bids allowed us to measure values expressed in behavior at the time of choice.

At the end of the experiment, food was auctioned using an adapted version of the Becker-DeGroot-Marschak auction (Becker et al., 1964; Plassmann et al., 2007). We gave 3 € to each subject to spend during the auction over a maximum of three trials. Snacks and snacks prices were randomly selected by drawing a paper from a bag. The bids on those trials during the fMRI task determined whether subjects got to eat that food.

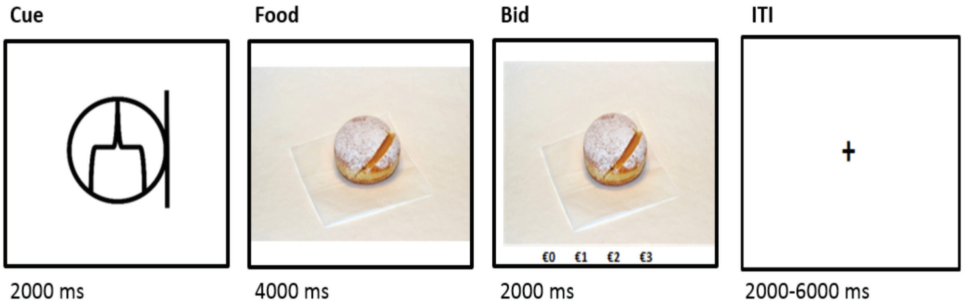

FIGURE 1 | Timing and structure of a trial from the functional magnetic resonance task. ITI, intertrial interval.

Consider b the bid made by the subject during the fMRI task. During the auction, a random price a was drawn (0 €, 1 €, 2 €, and 3 € were chosen with equal probability). If $b \geq a$, the participant got the item and spend a. If $b < a$, the subject did not get the item. The rules of the auction ensure the subjects' best strategy to bid their true value for each food. This was explained and emphasized during the instruction period. For auction effects, omissions resulted in a bid of 0 €.

fMRI Data Acquisition

Each participant was scanned on a clinical approved 1.5 T Siemens Magnetom Avanto system (Siemens Medical Solutions, Germany) using a 12-channel receive-only head array coil. For the functional acquisition, a T2* weighted echo-planar imaging acquisition was acquired: 38 interleaved axial slices, repetition time 2750 ms, echo time 30 ms, field of view 224 mm × 224 mm, flip angle 90°, in-plane resolution 3.5 mm × 3.5 mm, slice thickness 3.5 mm, and between-slice gap 0.5 mm. To optimize the sensitivity in the orbitofrontal cortex, a tilted acquisition in an oblique orientation of 30° relative to the anterior-posterior commissure line was used. In total, 650 volumes were acquired during the task. The task stimulus was presented using the fully integrated fMRI system IFIS-SA (Invivo Corporation, United States) and the same system was used to record the subject key-press responses. One high-resolution T1-weighted Magnetization-Prepared Rapid Acquisition with Gradient Echo sequence, with 1 mm × 1 mm × 1 mm voxel size, repetition time 2.73 s, echo time 3.48 ms, flip angle 7°, field of view 234 mm × 234 mm, and 176 slices was acquired. This anatomical sequence was used to project the functional maps.

fMRI Data Preprocessing

The functional scans from each participant were preprocessed using the Statistical Parametric Mapping (SPM) version 12 (Wellcome Department of Imaging Neuroscience, Institute of Neurology, United Kingdom) using MATLAB version R2018a (The MathWorks Inc.,United States). The preprocessing procedures included: slice-timing correction using the first slice as reference; realignment to the mean volume of the acquisition; nonlinear spatial normalization to Montreal Neurological Institute (MNI) standard space and resampling to 2 mm × 2 mm × 2 mm voxel size; spatial smoothing with a 8 mm full-width at half-maximum Gaussian kernel; high pass temporal filtering at 128 s. Participants with more than 3 mm of movement (1 voxel) were excluded ($n = 0$).

fMRI Data Analysis

For the first-level analysis, one general linear model (GLM) was computed per participant. For this GLM, the regressors of interest included: the type of cognitive regulation trial (1 – distance, 2 – natural, and 3 – indulge) and the corresponding bid (4 – bids after distance trials, 5 – bids after natural trials, and 6 – bids after indulge trials). The bid regressors were parametrically modulated by the bid value (0, 1, 2, and 3 €), the pre-rating score before the task (1 to 4), and the reaction time. Additional regressors included: 7 – the cue; 8 – the interstimulus interval; 9 – the omission bids; 10 – 16 the motion parameters estimated during the realignment step. The onset and duration of the regressors were defined accordingly to the stimulus represented in **Figure 1** with a boxcar function and the regressors were convolved with the canonical hemodynamic response function.

At the group level (second-level analysis), a random-effects analysis was performed using four different mixed-design ANOVA models: (1) represented the cognitive regulation during the task (enabled comparisons in average activation for each regulation trial between and within groups); (2) concerned the bidding/valuation during the task modulated by the bid value; (3) concerned the bidding/valuation during the task modulated by the pre-rating score; (4) concerned the bidding/valuation during the task modulated by the reaction time. Models (2) – (4) were used to test if food valuation was different between groups after distinct regulation trials. For all models, the group (stress vs. control) was introduced as the between-subject factor and each trial during cognitive regulation (distance vs. natural vs. indulge) as the within-subject factor. Age and education were used as covariates for all models. All models were implemented with the GLMFlex toolbox[1] which uses partitioned error terms for within-group and between-group comparisons, enabling the estimation of all the effects of interest with a single model.

Results were considered statistically significant after correcting for multiple comparisons using cluster correction

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[1] http://nmr.mgh.harvard.edu/harvardagingbrain/People/AaronSchultz/GLM_Flex.html

(minimum cluster size of 90 voxels). The minimum cluster size was determined with 3DClustSim (AFNI version 17.0.13; National Institute of Mental Health)[2]. This program determines a minimum cluster size with Monte Carlo Simulation to achieve a corrected significance of $p < 0.05$ with an initial voxel-wise threshold of $p < 0.001$. The Automated Anatomical Labeling plugin for SPM was used to classify the brain regions.

RESULTS

Psychological Assessment

The stress group revealed higher levels of perceived stress (mean ± standard deviation 15.07 ± 5.23) than the control group (8.64 ± 5.27) as assessed by PSS-10 [$t_{(27)} = 3.30$, $p = 0.003$, effect size $d = 1.27$]. No statistically significant differences were found for BAI ($U = 117.50$, $p = 0.591$) and BDI ($U = 134.00$, $p = 0.217$) between groups.

Blood Sampling

The ACTH levels before the fMRI session were similar between the two groups ($U = 81.50$, $p = 0.310$).

Cortisol serum levels were not statistically significantly different between groups [group $F_{(1,27)} = 0.45$, $p = 0.509$] nor within group before and after the fMRI session [group × time $F_{(1,27)} = 1.00 \times 10^{-3}$, $p = 0.971$]. However, cortisol levels decreased in both groups after the task [time $F_{(1,27)} = 10.08$, $p = 0.004$, effect size $\chi^2 = 0.27$].

Glucose serum levels were not statistically significantly different between groups [group $F_{(1,27)} = 0.40$, $p = 0.531$] and the pre and post-measurement were similar within groups [group × time $F_{(1,27)} = 0.18$, $p = 0.672$]. However, glucose levels decreased in both groups after the task [time $F_{(1,27)} = 8.44$, $p = 0.007$, $\chi^2 = 0.24$].

Insulin serum levels were not statistically significantly different between groups [group $F_{(1,27)} = 0.42$, $p = 0.522$] and the pre and post-measurement were similar within groups [group × time $F_{(1,27)} = 3.68$, $p = 0.066$]. However, insulin levels decreased in both groups after the task [time $F_{(1,27)} = 9.21$, $p = 0.005$, $\chi^2 = 0.25$].

Behavioral Analysis

Given the differences in age and education between groups, we used these variables as covariates when analyzing behavioral parameters.

We analyzed the reaction time between and within groups during the different regulation trials (distance, natural, and indulge). We found an interaction effect between the group and the reaction time across the different regulation conditions [group × condition $F_{(2,50)} = 4.00$, $p = 0.024$, $\chi^2 = 0.14$; **Table 1** represents the results for all between and within group factors and covariate effects]. *Post hoc* tests with repeated measures ANOVA demonstrated statistically significant reaction time differences within the control group [$F_{(1.42,18.43)} = 7.06$, $p = 0.010$, $\chi^2 = 0.35$, Greenhouse-Geisser correction for non-sphericity] and within the stress group [$F_{(1.34,18.82)} = 4.72$, $p = 0.033$, $\chi^2 = 0.25$, Greenhouse-Geisser correction for non-sphericity]. Paired t-tests with Bonferroni correction showed that the reaction time for natural trials was shorter than for distance [$t_{(13)} = 4.82$, $p = 0.001$, $d = 2.67$] and indulge trials [$t_{(13)} = 3.07$, $p = 0.027$, $d = 1.70$], and distance and indulge trials presented similar reaction times [$t_{(13)} = 1.00$, $p = 1.000$] in the control group. However, we did not find significant statistical differences in the stress group during post-hoc analysis [$1.00 \leq t_{(14)} \leq 2.36$, $0.099 \leq p \leq 1.000$] (**Figure 2**).

Taking into account that different instructions were given during the pre-rating (how much the participants want the food) and the bidding (how much the participants want to pay for the food), we separately analyzed differences between groups in the valuation score across the regulation conditions (distance, natural, and indulge) for pre and post-regulation scores (**Table 1** represents the results for all between and within group factors and covariate effects). During pre-rating, we did not find statistically significant differences between groups or within group in terms of food valuation across the conditions. Moreover, the valuation score varied similarly among the conditions for both groups. However, during bidding, we found differences between groups [group $F_{(1,25)} = 6.91$, $p = 0.014$, $\chi^2 = 0.22$] but not within group in terms of food valuation across the conditions. Moreover, the valuation score varied similarly among the conditions for both groups. The stress group had lower valuation scores (1.06 ± 0.36 €) during bidding in comparison to the control group (1.50 ± 0.36 €) (**Figure 3**).

Moreover, we also studied differences between groups in the number of responses for each bidding value after each cognitive regulation trial inside the scanner. We found a significant interaction effect between the group and the bid value [group × valuation $F_{(2.13,53.15)} = 3.89$, $p = 0.024$, $\chi^2 = 0.13$, Greenhouse-Geisser correction for non-sphericity; **Table 1** represents the results for all between and within group factors and covariate effects]. *Post hoc* tests with repeated measures ANOVA demonstrated that the control [$F_{(3,39)} = 9.61$, $p = 7.000 \times 10^{-5}$, $\chi^2 = 0.42$] and the stress group [$F_{(2.03,28.43)} = 9.04$, $p = 0.001$, $\chi^2 = 0.39$, Greenhouse-Geisser correction for non-sphericity] had a different number of responses across the bid values. Paired t-tests with Bonferroni correction demonstrated that on average the stress participants bided more often 0 [$t_{(14)} = 3.93$, $p = 0.009$, $d = 1.78$] and 1 € [$t_{(14)} = 3.38$, $p = 0.027$, $d = 1.81$] than 3 €, while control subjects bided more times 1 [$t_{(13)} = 3.94$, $p = 0.010$, $d = 2.18$] and 2 € [$t_{(13)} = 5.91$, $p = 3.090 \times 10^{-4}$, $d = 3.28$] than 3 € (**Figure 4**).

Neuroimaging Results

We tested for differences in blood-oxygen-level-dependent responses between stress and control groups during each cognitive regulation period/trial (natural, indulge, and distance) – model (1). No statistically significant brain regions were identified for overall differences between groups (main effect of group). When looking at the interaction effect between

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[2] https://afni.nimh.nih.gov/

TABLE 1 | Results for statistical tests on behavioral variables associated with the functional magnetic resonance imaging task: reaction time, valuation score, and response frequency.

Statistical effect	Test value	*P*-value	Effect size χ^2
Reaction time			
Condition (distance, natural, and indulge)	$F_{(2,50)} = 3.00$	0.059	
Group × condition	$F_{(2,50)} = 4.00$	0.024	0.14*
Group	$F_{(1,25)} = 0.02$	0.886	
Age	$F_{(1,25)} = 1.36 \times 10^{-4}$	0.991	
Education	$F_{(1,25)} = 0.40$	0.535	
Valuation score			
Pre-rating score			
Condition (distance, natural, and indulge)	$F_{(2,50)} = 1.21$	0.308	
Group × condition	$F_{(2,50)} = 0.85$	0.433	
Group	$F_{(1,25)} = 0.32$	0.574	
Age	$F_{(1,25)} = 0.03$	0.873	
Education	$F_{(1,25)} = 0.12$	0.728	
Bid value			
Condition (distance, natural, and indulge)	$F_{(1.32,33.03)} = 0.57$	0.502	
Group × condition	$F_{(1.32,33.03)} = 1.87$	0.180	
Group	$F_{(1,25)} = 6.91$	0.014	0.22*
Age	$F_{(1,25)} = 0.11$	0.746	
Education	$F_{(1,25)} = 0.56$	0.462	
Response frequency			
Condition (distance, natural, and indulge)	$F_{(1.16,29.0)} = 0.02$	0.912[a]	
Group × condition	$F_{(1.16,29.0)} = 0.03$	0.895[a]	
Valuation (0, 1, 2, and 3 €)	$F_{(2.13,53.15)} = 1.30$	0.283[a]	
Group × valuation	$F_{(2.13,53.15)} = 3.89$	0.024[a]	0.13*
Condition × valuation	$F_{(3.44,86.11)} = 0.76$	0.536[a]	
Group × condition × valuation	$F_{(3.44,86.11)} = 1.45$	0.231[a]	
Group	$F_{(1,25)} = 0.27$	0.605	
Age	$F_{(1,25)} = 0.20$	0.655	
Education	$F_{(1,25)} = 0.11$	0.747	

**Statistical significance;* [a]*Greenhouse-Geisser correction for non-sphericity.*

trial condition and group, there were also no statistically significant effects. Nonetheless, we found a main effect of the cognitive regulation condition in the left hemisphere in the superior (Brodmann area 22) and middle temporal gyrus (Brodmann area 21), the rolandic operculum, and the precentral gyrus (Brodmann area 6) [$7.87 \leq F_{(2,54)} \leq 13.97$, $p \leq 0.001$, 99 voxels, Montreal Neurological Institute peak voxel coordinates -60 -6 -4). *Post hoc* paired *t*-tests with Bonferroni correction demonstrated that the distance and indulge trials elicited lower activity than natural trials and that distance trials lead to higher responses than indulge trials in these regions [distance vs. natural $t_{(28)} = 2.97$, $p = 0.018$, $d = 1.12$; distance vs. indulge $t_{(28)} = 2.68$, $p = 0.036$, $d = 1.01$; natural vs. indulge $t_{(28)} = 4.97$, $p = 9 \times 10^{-5}$, $d = 1.88$] (**Figure 5**).

With the models (2) – (4), we tested if food valuation/bidding behavior was associated with different brain activation between groups after each regulation condition, with parametric modulation by bid value (model 2), pre-rating score (model 3), and reaction time (model 4). No statistically significant regions were identified for overall differences between groups during bidding (main effect of group) for the models (2) – (4). Additionally, no statistically significant active regions were found for interaction effects of group and the bids after each category of cognitive regulation (group × cognitive regulation condition), and the main effect of the condition was also not statistically significant for the models (2) – (4).

Task Validity

Given that our fMRI task was adapted from Hutcherson et al. (2012), here we compared our main results with these authors' significant findings to study the task validity. Since we observed behavioral differences between the control and stress groups, we assessed the validity of the task only with the control group.

As observed by Hutcherson et al. (2012), we also saw that the control group took longer while bidding after distance [$t_{(13)} = 4.82$, $p = 0.001$, $d = 2.67$, with Bonferroni correction] and indulge trials [$t_{(13)} = 3.07$, $p = 0.027$, $d = 1.70$, with Bonferroni correction] than natural trials [group × condition $F_{(1.42,18.43)} = 7.06$, $p = 0.010$, $\chi^2 = 0.35$, Greenhouse-Geisser correction for non-sphericity] (**Figure 2**). Moreover, the distance trials were also associated with the longest reaction time (778.30 ± 198.70 ms), followed by indulge (744.38 ± 125.21 ms),

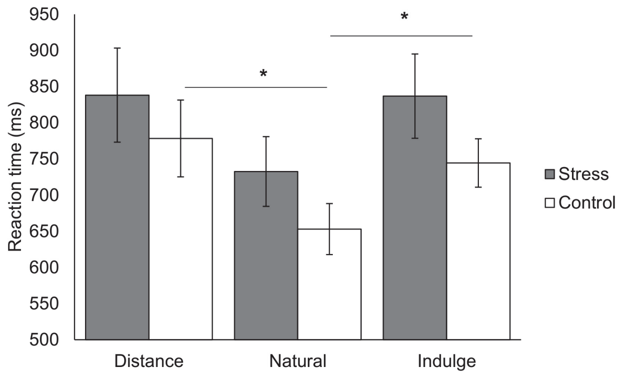

FIGURE 2 | Representation of the reaction time for the different regulation conditions (natural, distance, and indulge) for the stress and control group. The reaction time for natural trials was shorter than for distance [$t_{(13)}$ = 4.82, p = 0.001, d = 2.67] and indulge trials [$t_{(13)}$ = 3.07, p = 0.027, d = 1.70] in the control group but no statistically significant differences occurred in the stress group. The black star represents statistically significant differences. The main bars represent the mean values and the error bars represent the standard error.

and natural (652.98 ± 131.97 ms) trials. These reaction times values are consistent with the previous study.

Concerning the bid value, similarly to Hutcherson et al. (2012), we observed a main effect of the cognitive regulation condition (distance, natural, and indulge) in controls [$F_{(1.23,16.05)} = 16.88$, $p = 4.650 \times 10^{-4}$, $\chi^2 = 0.56$, Greenhouse-Geisser correction for non-sphericity]. The control participants bided higher on indulge [1.74 ± 0.43 €; $t_{(13)} = 2.89$, $p = 0.038$, $d = 1.60$, with Bonferroni correction] and lower on distance [1.04 ± 0.28 €; $t_{(13)} = 4.22$, $p = 0.003$, $d = 2.34$, with Bonferroni correction] compared to natural trials (1.50 ± 0.23 €). Bids after distance and indulge trials were also statistically significantly different [$t_{(13)} = 4.22$, $p = 0.003$, $d = 2.34$, with Bonferroni correction] (**Figure 3**). The bid values in our study (0, 1, 2, and 3 €) were distinct from the original study ($ 0.0, 0.5, 1.0, 1.5, 2.0, and 2.5), thus we could not compare the average bid values after each condition trial.

For neuroimaging data, we computed the contrasts among the cognitive regulation trials in the control group to compare our results with the original study: Distance > Natural, Natural > Distance, Indulge > Natural, Natural > Indulge, Distance > Indulge, and Indulge > Distance. We applied cluster correction for multiple comparisons (90 voxels as described in the section "Materials and Methods"). We found statistically significant results only for the contrasts Distance > Natural and Indulge > Natural. These results are in agreement with Hutcherson et al. (2012)'s findings if the same minimum cluster size is considered. For the contrast Distance > Natural, similarly to the original work, we also found statistically significant activation in temporal and posterior parietal regions (**Supplementary Table S1**). However, results did not show statistically significant activity in medial and ventrolateral prefrontal regions. For the contrast Indulge > Natural, we found statistically significant responses in the anterior cingulate cortex, the ventral, medial, and superior prefrontal cortex, temporal and parietal regions, and the supplementary motor area (**Supplementary Table S1**). Thus, our results are concordant with these authors' previous findings.

DISCUSSION

We studied how chronic stress influences decision-making on food valuation after cognitive regulation (increasing/indulge or decreasing/distance food craving) in medical students. Behavioral, biochemical and neuroimaging analysis were performed to address this question. We found that stressed participants present decreased food valuation scores. This result was reinforced by a higher number of responses for the lowest bid values for food in the stress group. The biochemical analysis (serum levels of insulin, cortisol, and glucose) did not show statistically significant differences between the control and stress group. The neuroimaging results did not demonstrate statistically significant differently activated brain regions between the stressed and control participants during cognitive regulation of craving and decision-making/bidding.

Although the acute stress response is generally beneficial, i.e., promotes adaptation to stressful stimulus, prolonged activation of the stress response produces deleterious effects on the body and brain, affecting cognitive processes such as decision-making (Mcewen, 2004; McEwen and Gianaros, 2011; Sousa, 2016). One of the main findings of the present study is that stressed individuals presented lower scores during food valuation, in contrast with our initial hypothesis. This may translate a blunted hedonic capacity or reward sensitivity (Berenbaum and Connelly, 1993; Porcelli et al., 2012; Bryce and Floresco, 2016; Porcelli and Delgado, 2017; Uy and Galván, 2017), as anhedonia has been associated with higher perceived stress scale scores (Pizzagalli et al., 2007) and stress causes changes in regions related to hedonic/rewarding behavior such as the amygdala, orbitofrontal cortex, vmPFC, and ventral and dorsal striatum (Gorwood, 2008; Porcelli et al., 2012; Bessa et al., 2013; Stark et al., 2015). Moreover, the distribution of the number of responses was higher for lower bids in the stress group, i.e., stressed subjects seemed less prone to place high bids for food. A previous work including a food-related task discovered decreased reward sensitivity associated with alterations in the putamen activity after acute stress induction (Born et al., 2010). Another report pointed out that acute stress does not potentiate craving after stimulation with food pictures (Stojek et al., 2015). Moreover, animal research indicates that acute stress reduces the motivation to work for food rewards (Bryce and Floresco, 2016). Other studies have also shown that acute and chronic stress mitigate brain responses to food stimuli in reward pathways (Wierenga et al., 2018). These results support the idea that stress participants have a reduced valuation attributed to food rewards. However, other studies have shown increased sensitivity to high-caloric food rewards in stressed individuals (Razzoli et al., 2017; Ans et al., 2018; Berg Schmidt et al., 2018; Ferrer-Cascales et al., 2018). Reward processing might be different when participants are stimulated with food pictures or real food. Moreover, the inclusion of chronic or acute stress

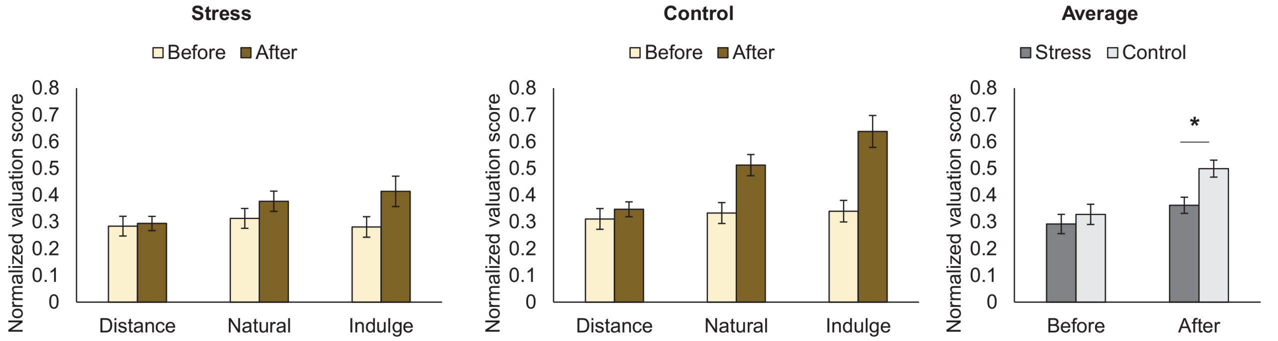

FIGURE 3 | Representation of the normalized rating scores for food pictures for each trial condition (natural, distance, and indulge) before performing the functional magnetic resonance task (before cognitive regulation) and during the functional magnetic resonance task (after cognitive regulation) for the stress and control groups (the normalized scores represent the ratio between given score and maximum score). Before cognitive regulation, we did not find statistically significant differences between groups or within group in terms of food valuation across the conditions. After cognitive regulation, the stress group had lower average valuation scores in comparison to the control group [group $F_{(1,25)} = 6.91$, $p = 0.014$, $\chi^2 = 0.22$]. The black star represents statistically significant differences. The main bars represent the mean values and the error bars represent the standard error.

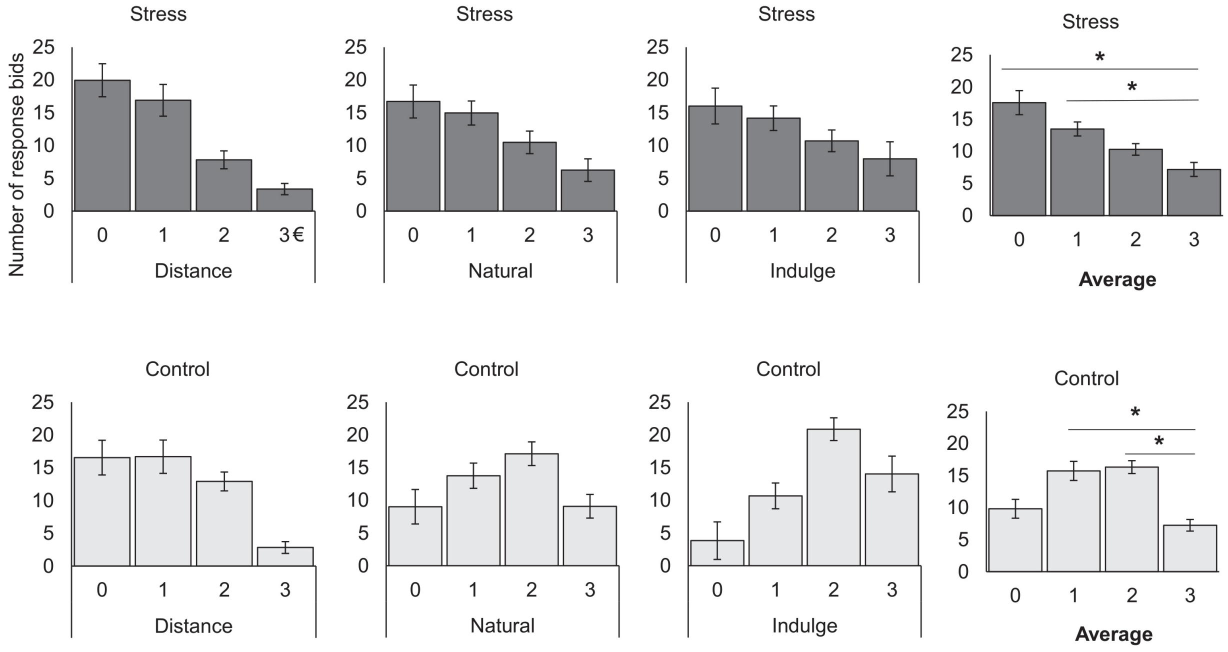

FIGURE 4 | Representation of the number of responses for the stress and control groups during bidding for each cognitive regulation trial and for the average of all trials. On average, the stress participants bided more often 0 [$t_{(14)} = 3.93$, $p = 0.009$, $d = 1.78$] and 1 € [$t_{(14)} = 3.38$, $p = 0.027$, $d = 1.81$] than 3 €, while control subjects bided more times 1 [$t_{(13)} = 3.94$, $p = 0.010$, $d = 2.18$] and 2 € [$t_{(13)} = 5.91$, $p = 3.090 \times 10^{-4}$, $d = 3.28$] than 3 €. The black star represents statistically significant differences. The main bars represent the mean values and the error bars represent the standard error.

models might also account for different results regarding reward sensitivity (Porcelli and Delgado, 2017). However, our results need confirmation with larger sample sizes.

While bidding, the stressed subjects did not present differential brain activity when compared to control subjects, despite the behavioral differences in the valuation score. We were expecting that poor cognitive self-control reflected in reduced prefrontal activation (Hare et al., 2009, 2011; Kober et al., 2010; Hutcherson et al., 2012) would lead to higher responses in striatal and amygdalar regions associated with increased reward sensitivity (Louis et al., 2009; Tryon et al., 2013; Maier et al., 2015; Neseliler et al., 2017). Other studies have found controversial results demonstrating that reduced striatal activity was associated with high levels of stress and increased food craving (Hommer et al., 2013). However, we did not observe cognitive differences between the groups and reward sensitivity was decreased. Our sample size may have limited the statistical power of this analysis. Thus, further research should be conducted to understand the neural correlates of decision-making after cognitive regulation since our results are not conclusive.

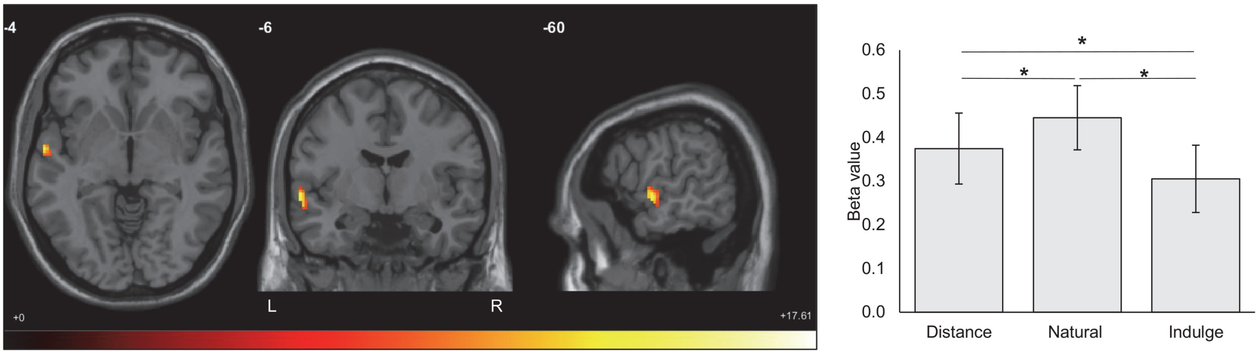

FIGURE 5 | Statistically significant brain regions resulting from the main effect of the cognitive regulation condition (natural, indulge, and distance) for both groups (cluster correction for multiple comparisons, minimum voxel size of 90, $p < 0.001$, $F_{(2,54)}$ value between 7.87 and 13.97 represented by the colored bar). The distance and indulge trials elicited lower activity than natural trials, and the distance trials lead to higher responses than indulge trials in these regions (distance vs. natural $t_{(28)} = 2.97$, $p = 0.018$, $d = 1.12$; distance vs. indulge $t_{(28)} = 2.68$, $p = 0.036$, $d = 1.01$; natural vs. indulge $t_{(28)} = 4.97$, $p = 9 \times 10^{-5}$, $d = 1.88$). These regions include the superior (Brodmann area 22) and middle temporal gyrus (Brodmann area 21), the rolandic operculum, and the precentral gyrus (Brodmann area 6). The numbers above the slices represent the Montreal Neurological Institute peak voxel coordinates. The black star represents statistically significant differences. The main bars represent the mean values and the error bars represent the standard error. L, left; R, Right.

Our neuroimaging results did not show brain activity differences between groups during cognitive regulation. According to previous studies, the vmPFC and dlPFC are regions responsible for cognitive regulation in this decision-making context (Hare et al., 2009, 2011; Kober et al., 2010; Hutcherson et al., 2012). Thus, the absence of changes in these regions between groups in our work might indicate that the processes for cognitive regulation of food craving are not affected by chronic stress, or that our specific model of chronic stress might not lead to changes in cognitive modulation of craving. However, previous works revealed that cognitive control is diminished under stress, leading to emotional and habitual-biased decision-making (Yu, 2016), and increased reward sensitivity for food (Tryon et al., 2013; Maier et al., 2015; Neseliler et al., 2017). Our moderate sample size might have hindered putative differences between groups. Nonetheless, as shown in **Figures 2**, **3**, stressed participants were able to modulate their responses, demonstrating an effective cognitive regulation, although the average food bidding score was lower than in controls. Both groups were capable of effectively using cognitive regulation to change the value placed on food during regulated trials. Moreover, both groups took longer times during bidding after regulated trials. Indeed, we found that activity in the superior and middle temporal gyrus, rolandic operculum, and precentral gyrus was differently modulated by trials with cognitive regulation of craving versus non-regulated trials in both groups. Previous authors provided evidence for a functional connection between the vmPFC and the precentral gyrus during food-related decisions, and for the correlation between food ratings and the response in the middle temporal gyrus (Kober et al., 2010; Hare et al., 2011; Hutcherson et al., 2012). Moreover, the temporal gyrus is also involved in food imagery (Hommer et al., 2013). Thus, the regulatory success does not seem to be affected by stress. During cognitive control tasks, attentional narrowing might occur after stimulation with negative pictures with threat and sadness-related content (van Steenbergen et al., 2011; Melcher et al., 2012; Papazacharias et al., 2015). Thus, the negative emotional state in the stress group (e.g., fear of falling the final exam) might have led to higher attentional focus during cognitive regulation that might compensate cognitive deficits associated with chronic stress. Nonetheless, our results need further validation with larger sample sizes to rule out a putative effect of chronic stress in cognitive regulation of craving.

Insulin, cortisol, and glucose levels are expected to decrease after fasting (Kirschbaum et al., 1997; Adam and Epel, 2007; Figlewicz, 2015; Tiedemann et al., 2017). However, peripheral concentrations of cortisol rise after stimulation with food images due to appetite enhancement, while insulin and glucose levels seem to be unaffected (Schmid et al., 2005; Schüssler et al., 2012; Kroemer et al., 2013). In our study, both groups presented a decreased in insulin, glucose, and cortisol levels after the fMRI task. Thus, the effects of fasting might have potentially surpassed the effects of stimulation with food pictures (Brede et al., 2017). Nonetheless, this hypothesis needs further testing. We were expecting increased craving in the stress group after a deficient cognitive regulation and increased reward sensitivity to food (Tryon et al., 2013; Maier et al., 2015; Neseliler et al., 2017). However, our results agree with the fact that we found reduced valuation of rewards in the absence of cognitive regulation alterations in the stress group, suggesting that overall craving was reduced. For controls, the instructions to differently modulate craving might have led to balanced changes in blood parameters after stimulation with food pictures. Thus, our results might derive from fasting since they occurred in both groups.

Importantly, our results are limited by the sample size. These results need to be replicated with larger samples to avoid false negative and positive conclusions. Moreover, the results might have been influenced by the unbalanced proportion of females and males per group, given that gender differences were found in decision-making under stress (Yu, 2016; Wemm and Wulfert, 2017). However, we focused on group differences and groups were matched for gender ratio.

Our results show that the capacity to perform cognitive regulation of craving is not impaired after prolonged stress. However, chronic stress reduces the value attributed to food rewards after craving modulation. Importantly, our conclusions are limited by the small sample size and need further validation with larger samples. These findings are relevant to guide subsequent studies on cognitive regulation of food-related decision-making for eating and obesity-associated disorders. Cognitive control techniques might be used to tackle decision-making impairments in these conditions (Louis et al., 2009; May et al., 2012).

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 Declaration of Helsinki. All subjects gave written informed consent. The protocol was approved by the Ethics Subcommittee for the Life and Health Sciences of University of Minho, Portugal, and by the Ethics Committee of the Hospital of Braga, Portugal.

AUTHOR CONTRIBUTIONS

SF, CV, PM, RM, AC, PMore, and CP-N acquired, analyzed, and interpreted the data and wrote the manuscript. NS and PMorg supervised the work, interpreted the data, and wrote and reviewed the manuscript. All authors participated in the design of the experiments and approved the manuscript.

FUNDING

This work was funded by the MyHealth project (DoIT – Desenvolvimento e Operacionalização da Investigação de Translação, Contract DoIT-13853) and the BIAL Foundation, Porto, Portugal (Grant No. PT/FB/BL-2016-206). This work was also funded by the FEDER funds, through the Competitiveness Factors Operational Programme (COMPETE), and by national funds, through the Foundation for Science and Technology (FCT), under the scope of the project POCI-01-0145-FEDER-007038. This manuscript has been developed under the scope of the project NORTE-01-0145-FEDER-000013, supported by the Northern Portugal Regional Operational Programme (NORTE 2020), under the Portugal 2020 Partnership Agreement, through the European Regional Development Fund (FEDER). PaM was supported by a fellowship of the project "SwitchBox" (Contract HEALTH-F2-2010-259772). SF was supported by a combined Ph.D. scholarship from the FCT and the company iCognitus4ALL – IT Solutions, Lda (PD/BDE/127839/2016). RM was supported by the combined FCT and Enlightenment, Lda fellowship (PDE/BDE/113604/2015) from the PhDiHES program.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fnins.2019.00724/full#supplementary-material

REFERENCES

Adam, T. C., and Epel, E. S. (2007). Stress, eating and the reward system. *Physiol. Behav.* 91, 449–458. doi: 10.1016/j.physbeh.2007.04.011

Ans, A. H., Anjum, I., Satija, V., Inayat, A., Asghar, Z., Akram, I., et al. (2018). Neurohormonal regulation of appetite and its relationship with stress: a mini literature review. *Cureus* 10:e3032. doi: 10.7759/cureus.3032

Arnsten, A. F. T. (2015). Stress weakens prefrontal networks: molecular insults to higher cognition. *Nat. Neurosci.* 18, 1376–1385. doi: 10.1038/nn.4087

Balleine, B. (2005). Neural bases of food-seeking: affect, arousal and reward in corticostriatolimbic circuits?. *Physiol. Behav.* 86, 717–730. doi: 10.1016/j.physbeh.2005.08.061

Basten, U., Biele, G., Heekeren, H. R., and Fiebach, C. J. (2010). How the brain integrates costs and benefits during decision making. *Proc. Natl. Acad. Sci. U.S.A.* 107, 21767–21772. doi: 10.1073/pnas.0908104107

Beck, A. T., Epstein, N., Brown, G., and Steer, R. A. (1988). An inventory for measuring clinical anxiety: psychometric properties. *J. Consult. Clin. Psychol.* 56, 893–897. doi: 10.1037/0022-006X.56.6.893

Beck, A. T., Steer, R. A., Ball, R., and Ranieri, W. (1996). Comparison of beck depression inventories -IA and -II in psychiatric outpatients. *J. Pers. Assess.* 67, 588–597. doi: 10.1207/s15327752jpa6703_13

Becker, G. M., Degroot, M. H., and Marschak, J. (1964). Measuring utility by a single-response sequential method. *Behav. Sci.* 9, 226–232. doi: 10.1002/bs.3830090304

Berenbaum, H., and Connelly, J. (1993). The effect of stress on hedonic capacity. *J. Abnorm. Psychol.* 102, 474–481. doi: 10.1037/0021-843X.102.3.474

Berg Schmidt, J., Johanneson Bertolt, C., Sjödin, A., Ackermann, F., Vibeke Schmedes, A., Lynge Thomsen, H., et al. (2018). Does stress affect food preferences? – a randomized controlled trial investigating the effect of examination stress on measures of food preferences and obesogenic behavior. *Stress* 21, 556–563. doi: 10.1080/10253890.2018.1494149

Bessa, J. M., Morais, M., Marques, F., Pinto, L., Palha, J. A., Almeida, O. F. X., et al. (2013). Stress-induced anhedonia is associated with hypertrophy of medium spiny neurons of the nucleus accumbens. *Transl. Psychiatry* 3, e266–e266. doi: 10.1038/tp.2013.39

Born, J. M., Lemmens, S. G. T., Rutters, F., Nieuwenhuizen, A. G., Formisano, E., Goebel, R., et al. (2010). Acute stress and food-related reward activation in the brain during food choice during eating in the absence of hunger. *Int. J. Obes.* 34, 172–181. doi: 10.1038/ijo.2009.221

Brede, S., Sputh, A., Hartmann, A.-C., Hallschmid, M., Lehnert, H., and Klement, J. (2017). Visual food cues decrease postprandial glucose concentrations in lean and obese men without affecting food intake and related endocrine parameters. *Appetite* 117, 255–262. doi: 10.1016/j.appet.2017.07.001

Bryce, C. A., and Floresco, S. B. (2016). Perturbations in effort-related decision-making driven by acute stress and corticotropin-releasing factor. *Neuropsychopharmacology* 41, 2147–2159. doi: 10.1038/npp.2016.15

Chen, Y., and Baram, T. Z. (2016). Toward understanding how early-life stress reprograms cognitive and emotional brain networks. *Neuropsychopharmacology* 41, 197–206. doi: 10.1038/npp.2015.181

Christopoulos, G. I., Tobler, P. N., Bossaerts, P., Dolan, R. J., and Schultz, W. (2009). Neural correlates of value. risk, and risk aversion contributing to decision making under risk. *J. Neurosci.* 29, 12574–12583. doi: 10.1523/JNEUROSCI.2614-09.2009

Cohen, S., Kamarck, T., and Mermelstein, R. (1983). A global measure of perceived stress. *J. Health Soc. Behav.* 24:385. doi: 10.2307/2136404

Delgado, M. R., Gillis, M. M., and Phelps, E. A. (2008). Regulating the expectation of reward via cognitive strategies. *Nat. Neurosci.* 11, 880–881. doi: 10.1038/nn.2141

Dias-Ferreira, E., Sousa, J. C., Melo, I., Morgado, P., Mesquita, A. R., Cerqueira, J. J., et al. (2009). Chronic stress causes frontostriatal reorganization and affects decision-making. *Science* 325, 621–625. doi: 10.1126/science.1171203

Fehr, E., and Camerer, C. F. (2007). Social neuroeconomics: the neural circuitry of social preferences. *Trends Cogn. Sci.* 11, 419–427. doi: 10.1016/j.tics.2007.09.002

Ferrer-Cascales, R., Albaladejo-Blázquez, N., Ruiz-Robledillo, N., Rubio-Aparicio, M., Laguna-Pérez, A., and Zaragoza-Martí, A. (2018). Low adherence to the mediterranean diet in isolated adolescents: the mediation effects of stress. *Nutrients* 10:1894. doi: 10.3390/nu10121894

Figlewicz, D. P. (2015). Modulation of food reward by endocrine and environmental factors. *Psychosom. Med.* 77, 664–670. doi: 10.1097/PSY.0000000000000146

Gold, J. I., and Shadlen, M. N. (2007). The neural basis of decision making. *Annu. Rev. Neurosci.* 30, 535–574. doi: 10.1146/annurev.neuro.29.051605.113038

Gorwood, P. (2008). Neurobiological mechanisms of anhedonia. *Dialogues Clin. Neurosci.* 10, 291–299.

Hare, T. A., Camerer, C. F., and Rangel, A. (2009). Self-control in decision-making involves modulation of the vmpfc valuation system. *Science* 324, 646–648. doi: 10.1126/science.1168450

Hare, T. A., Malmaud, J., and Rangel, A. (2011). Focusing attention on the health aspects of foods changes value signals in vmpfc and improves dietary choice. *J. Neurosci.* 31, 11077–11087. doi: 10.1523/JNEUROSCI.6383-10.2011

Hommer, R. E., Seo, D., Lacadie, C. M., Chaplin, T. M., Mayes, L. C., Sinha, R., et al. (2013). Neural correlates of stress and favorite-food cue exposure in adolescents: a functional magnetic resonance imaging study. *Hum. Brain Mapp.* 34, 2561–2573. doi: 10.1002/hbm.22089

Hutcherson, C. A., Plassmann, H., Gross, J. J., and Rangel, A. (2012). Cognitive regulation during decision making shifts behavioral control between ventromedial and dorsolateral prefrontal value systems. *J. Neurosci.* 32, 13543–13554. doi: 10.1523/JNEUROSCI.6387-11.2012

Kirschbaum, C., Bono, E. G., Rohleder, N., Gessner, C., Pirke, K. M., Salvador, A., et al. (1997). Effects of fasting and glucose load on free cortisol responses to stress and nicotine. *J. Clin. Endocrinol. Metab.* 82, 1101–1105. doi: 10.1210/jcem.82.4.3882

Kober, H., Mende-Siedlecki, P., Kross, E. F., Weber, J., Mischel, W., Hart, C. L., et al. (2010). Prefrontal-striatal pathway underlies cognitive regulation of craving. *Proc. Natl. Acad. Sci. U.S.A.* 107, 14811–14816. doi: 10.1073/pnas.1007779107

Kroemer, N. B., Krebs, L., Kobiella, A., Grimm, O., Vollstädt-Klein, S., Wolfensteller, U., et al. (2013). (Still) longing for food: insulin reactivity modulates response to food pictures. *Hum. Brain Mapp.* 34, 2367–2380. doi: 10.1002/hbm.22071

Louis, W. R., Chan, M. K.-H., and Greenbaum, S. (2009). Stress and the theory of planned behavior: understanding healthy and unhealthy eating intentions. *J. Appl. Soc. Psychol.* 39, 472–493. doi: 10.1111/j.1559-1816.2008.00447.x

Magalhães, R., Barrière, D. A., Novais, A., Marques, F., Marques, P., Cerqueira, J., et al. (2018). The dynamics of stress: a longitudinal MRI study of rat brain structure and connectome. *Mol. Psychiatry* 23, 1998–2006. doi: 10.1038/mp.2017.244

Maier, S. U., Makwana, A. B., and Hare, T. A. (2015). Acute stress impairs self-control in goal-directed choice by altering multiple functional connections within the brain's decision circuits. *Neuron* 87, 621–631. doi: 10.1016/j.neuron.2015.07.005

May, J., Andrade, J., Kavanagh, D. J., and Hetherington, M. (2012). Elaborated intrusion theory: a cognitive-emotional theory of food craving. *Curr. Obes. Rep.* 1, 114–121. doi: 10.1007/s13679-012-0010-12

Mcewen, B. S. (2004). Protection and damage from acute and chronic stress: allostasis and allostatic overload and relevance to the pathophysiology of psychiatric disorders. *Ann. N. Y. Acad. Sci.* 1032, 1–7. doi: 10.1196/annals.1314.001

McEwen, B. S., and Gianaros, P. J. (2011). Stress- and allostasis-induced brain plasticity. *Annu. Rev. Med.* 62, 431–445. doi: 10.1146/annurev-med-052209-100430

McGuire, J. T., and Kable, J. W. (2012). Decision makers calibrate behavioral persistence on the basis of time-interval experience. *Cognition* 124, 216–226. doi: 10.1016/j.cognition.2012.03.008

Melcher, T., Obst, K., Mann, A., Paulus, C., and Gruber, O. (2012). Antagonistic modulatory influences of negative affect on cognitive control: Reduced and enhanced interference resolution capability after the induction of fear and sadness. *Acta Psychol.* 139, 507–514. doi: 10.1016/j.actpsy.2012.01.012

Minkley, N., and Kirchner, W. H. (2012). Influence of test tasks with different cognitive demands on salivary cortisol concentrations in school students. *Int. J. Psychophysiol.* 86, 245–250. doi: 10.1016/j.ijpsycho.2012.09.015

Morgado, P., Freitas, D., Bessa, J. M., Sousa, N., and Cerqueira, J. J. (2013). Perceived stress in obsessive–compulsive disorder is related with obsessive but not compulsive symptoms. *Front. Psychiatry* 4:21. doi: 10.3389/fpsyt.2013.00021

Morgado, P., Marques, F., Ribeiro, B., Leite-Almeida, H., Pêgo, J. M., Rodrigues, A. J., et al. (2015a). Stress induced risk-aversion is reverted by D2/D3 agonist in the rat. *Eur. Neuropsychopharmacol.* 25, 1744–1752. doi: 10.1016/j.euroneuro.2015.07.003

Morgado, P., Sousa, N., and Cerqueira, J. J. (2015b). The impact of stress in decision making in the context of uncertainty. *J. Neurosci. Res.* 93, 839–847. doi: 10.1002/jnr.23521

Morgado, P., Silva, M., Sousa, N., and Cerqueira, J. J. (2012). Stress transiently affects pavlovian-to-instrumental transfer. *Front. Neurosci.* 6:93. doi: 10.3389/fnins.2012.00093

Neseliler, S., Tannenbaum, B., Zacchia, M., Larcher, K., Coulter, K., Lamarche, M., et al. (2017). Academic stress and personality interact to increase the neural response to high-calorie food cues. *Appetite* 116, 306–314. doi: 10.1016/j.appet.2017.05.016

Ochsner, K. N., Ray, R. D., Cooper, J. C., Robertson, E. R., Chopra, S., Gabrieli, J. D. E., et al. (2004). For better or for worse: neural systems supporting the cognitive down- and up-regulation of negative emotion. *Neuroimage* 23, 483–499. doi: 10.1016/j.neuroimage.2004.06.030

Papazacharias, A., Taurisano, P., Fazio, L., Gelao, B., Di Giorgio, A., Lo Bianco, L., et al. (2015). Aversive emotional interference impacts behavior and prefronto-striatal activity during increasing attentional control. *Front. Behav. Neurosci.* 9:97. doi: 10.3389/fnbeh.2015.00097

Phillips, M. L., Drevets, W. C., Rauch, S. L., and Lane, R. (2003). Neurobiology of emotion perception II: implications for major psychiatric disorders. *Biol. Psychiatry* 54, 515–528. doi: 10.1016/S0006-3223(03)00171-179

Pizzagalli, D. A., Bogdan, R., Ratner, K. G., and Jahn, A. L. (2007). Increased perceived stress is associated with blunted hedonic capacity: Potential implications for depression research. *Behav. Res. Ther.* 45, 2742–2753. doi: 10.1016/j.brat.2007.07.013

Plassmann, H., O'Doherty, J., and Rangel, A. (2007). Orbitofrontal cortex encodes willingness to pay in everyday economic transactions. *J. Neurosci.* 27, 9984–9988. doi: 10.1523/JNEUROSCI.2131-07.2007

Platt, M. L., and Huettel, S. A. (2008). Risky business: the neuroeconomics of decision making under uncertainty. *Nat. Neurosci.* 11, 398–403. doi: 10.1038/nn2062

Porcelli, A. J., and Delgado, M. R. (2017). Stress and decision making: effects on valuation, learning, and risk-taking. *Curr. Opin. Behav. Sci.* 14, 33–39. doi: 10.1016/j.cobeha.2016.11.015

Porcelli, A. J., Lewis, A. H., and Delgado, M. R. (2012). Acute stress influences neural circuits of reward processing. *Front. Neurosci.* 6:157. doi: 10.3389/fnins.2012.00157

Rangel, A., Camerer, C., and Montague, P. R. (2008). A framework for studying the neurobiology of value-based decision making. *Nat. Rev. Neurosci.* 9, 545–556. doi: 10.1038/nrn2357

Razzoli, M., Pearson, C., Crow, S., and Bartolomucci, A. (2017). Stress, overeating, and obesity: insights from human studies and preclinical models. *Neurosci. Biobehav. Rev.* 76, 154–162. doi: 10.1016/j.neubiorev.2017.01.026

Sandi, C. (2013). Stress and cognition. *Wiley Interdiscip. Rev. Cogn. Sci.* 4, 245–261. doi: 10.1002/wcs.1222

Schmid, D. A., Held, K., Ising, M., Uhr, M., Weikel, J. C., and Steiger, A. (2005). Ghrelin stimulates appetite. imagination of food, gh, acth, and cortisol, but does not affect leptin in normal controls. *Neuropsychopharmacology* 30, 1187–1192. doi: 10.1038/sj.npp.1300670

Schüssler, P., Kluge, M., Yassouridis, A., Dresler, M., Uhr, M., and Steiger, A. (2012). Ghrelin levels increase after pictures showing food. *Obesity* 20, 1212–1217. doi: 10.1038/oby.2011.385

Soares, J. M., Sampaio, A., Ferreira, L. M., Santos, N. C., Marques, F., Palha, J. A., et al. (2012). Stress-induced changes in human decision-making are reversible. *Transl. Psychiatry* 2, e131–e131. doi: 10.1038/tp.2012.59

Sousa, N. (2016). The dynamics of the stress neuromatrix. *Mol. Psychiatry* 21, 302–312. doi: 10.1038/mp.2015.196

Starcke, K., and Brand, M. (2012). Decision making under stress: A selective review. *Neurosci. Biobehav. Rev.* 36, 1228–1248. doi: 10.1016/j.neubiorev.2012.02.003

Stark, E. A., Parsons, C. E., Van Hartevelt, T. J., Charquero-Ballester, M., McManners, H., Ehlers, A., et al. (2015). Post-traumatic stress influences the brain even in the absence of symptoms: a systematic, quantitative meta-analysis of neuroimaging studies. *Neurosci. Biobehav. Rev.* 56, 207–221. doi: 10.1016/j.neubiorev.2015.07.007

Stojek, M. K., Fischer, S., and MacKillop, J. (2015). Stress, cues, and eating behavior. Using drug addiction paradigms to understand motivation for food. *Appetite* 92, 252–260. doi: 10.1016/j.appet.2015.05.027

Tiedemann, L. J., Schmid, S. M., Hettel, J., Giesen, K., Francke, P., Büchel, C., et al. (2017). Central insulin modulates food valuation via mesolimbic pathways. *Nat. Commun.* 8:16052. doi: 10.1038/ncomms16052

Tryon, M. S., Carter, C. S., DeCant, R., and Laugero, K. D. (2013). Chronic stress exposure may affect the brain's response to high calorie food cues and predispose to obesogenic eating habits. *Physiol. Behav.* 120, 233–242. doi: 10.1016/j.physbeh.2013.08.010

Uy, J. P., and Galván, A. (2017). Acute stress increases risky decisions and dampens prefrontal activation among adolescent boys. *Neuroimage* 146, 679–689. doi: 10.1016/j.neuroimage.2016.08.067

van Steenbergen, H., Band, G. P. H., and Hommel, B. (2011). Threat but not arousal narrows attention: evidence from pupil dilation and saccade control. *Front. Psychol.* 2:281. doi: 10.3389/fpsyg.2011.00281

Wager, T. D., Davidson, M. L., Hughes, B. L., Lindquist, M. A., and Ochsner, K. N. (2008). Prefrontal-subcortical pathways mediating successful emotion regulation. *Neuron* 59, 1037–1050. doi: 10.1016/j.neuron.2008.09.006

Wemm, S. E., and Wulfert, E. (2017). Effects of acute stress on decision making. *Appl. Psychophysiol. Biofeedback* 42, 1–12. doi: 10.1007/s10484-016-9347-9348

Wierenga, C. E., Lavender, J. M., and Hays, C. C. (2018). The potential of calibrated fMRI in the understanding of stress in eating disorders. *Neurobiol. Stress* 9, 64–73. doi: 10.1016/j.ynstr.2018.08.006

Yu, R. (2016). Stress potentiates decision biases: A stress induced deliberation-to-intuition (SIDI) model. *Neurobiol. Stress* 3, 83–95. doi: 10.1016/j.ynstr.2015.12.006

Conflict of Interest Statement: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Neuroscience

CORRECTION
published: 22 November 2019
doi: 10.3389/fnins.2019.01252

Corrigendum: Reduced Hedonic Valuation of Rewards and Unaffected Cognitive Regulation in Chronic Stress

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Keywords: stress, decision-making, cognition, magnetic resonance imaging, fMRI, reward, human, food

A Corrigendum on

Reduced Hedonic Valuation of Rewards and Unaffected Cognitive Regulation in Chronic Stress
by Ferreira, S., Veiga, C., Moreira, P., Magalhães, R., Coelho, A., Marques, P., et al. (2019). Front. Neurosci. 13:724. doi: 10.3389/fnins.2019.00724

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Approved by:
Frontiers Editorial Office,
Frontiers Media SA, Switzerland

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Specialty section:
This article was submitted to Decision Neuroscience, a section of the journal Frontiers in Neuroscience

Received: *04 November 2019*
Accepted: *05 November 2019*
Published: *22 November 2019*

Citation:
Ferreira S, Veiga C, Moreira P, Magalhães R, Coelho A, Marques P, Portugal-Nunes C, Sousa N and Morgado P (2019) Corrigendum: Reduced Hedonic Valuation of Rewards and Unaffected Cognitive Regulation in Chronic Stress. Front. Neurosci. 13:1252. doi: 10.3389/fnins.2019.01252

In the original article, there was an error. The psychometric scale used to measure the depression scores was the "Beck Depression Inventory" and not the "Beck Depression Inventory II."

A correction has been made to the **Materials and Methods**, subsection **Sociodemographic and Psychological Scales**:

"Subjects filled a questionnaire to characterize gender, age, educational level, handedness, and ethnic origin. Weight and height were also measured to prevent the inclusion of participants with an unhealthy body mass index. Subjects were assessed with the 10-items Perceived Stress Scale (PSS-10) (Cohen et al., 1983; Morgado et al., 2013), the Beck Anxiety Inventory (BAI) (Beck et al., 1988), and the Beck Depression Inventory (BDI) (Beck et al., 1996). PSS-10 measures the extent to which participants perceived their life as unpredictable, uncontrollable, and overloaded during the previous month. The higher the score, the greater the intensity of perceived stress. BAI measures the severity of an individual's anxiety during the previous week. Scores lower than 8 indicate minimal anxiety. Scores higher than 7, 15, and 25 indicate mild, moderate, and severe anxiety, respectively. BDI measures the severity of depression and can be used as a screening tool. Scores lower than 14 indicate minimal depression. Higher scores indicate more severe depressive symptoms."

A correction has also been made to **Results**, subsection **Psychological Assessment**:

"The stress group revealed higher levels of perceived stress (mean ± standard deviation 15.07 ± 5.23) than the control group (8.64 ± 5.27) as assessed by PSS-10 [$t_{(27)} = 3.30$, $p = 0.003$, effect size $d = 1.27$]. No statistically significant differences were found for BAI ($U = 117.50$, $p = 0.591$) and BDI ($U = 134.00$, $p = 0.217$) between groups."

Lastly, a correction has been made to the **Abbreviations** section:

"ACTH, adrenocorticotropic hormone; BAI, Beck Anxiety Inventory; BDI, Beck Depression Inventory; dlPFC, dorsolateral prefrontal cortex; fMRI, functional magnetic resonance imaging; GLM, general linear model; MNI, Montreal Neurological Institute; PSS-10, 10-items Perceived Stress Scale; vmPFC, ventromedial prefrontal cortex."

The authors apologize for this error and state that this does not change the scientific conclusions of the article in any way. The original article has been updated.

REFERENCES

Beck, A. T., Epstein, N., Brown, G., and Steer, R. A. (1988). An inventory for measuring clinical anxiety: psychometric properties. *J. Consult. Clin. Psychol.* 56, 893–897. doi: 10.1037/0022-006X.56.6.893

Beck, A. T., Steer, R. A., Ball, R., and Ranieri, W. (1996). Comparison of beck depression inventories -IA and -II in psychiatric outpatients. *J. Pers. Assess.* 67, 588–597. doi: 10.1207/s15327752jpa6703_13

Cohen, S., Kamarck, T., and Mermelstein, R. (1983). A global measure of perceived stress. *J. Health Soc. Behav.* 24:385. doi: 10.2307/2136404

Morgado, P., Freitas, D., Bessa, J. M., Sousa, N., and Cerqueira, J. J. (2013). Perceived stress in obsessive–compulsive disorder is related with obsessive but not compulsive symptoms. *Front. Psychiatry* 4:21. doi: 10.3389/fpsyt.2013.00021

frontiers
in Psychology

ORIGINAL RESEARCH
published: 06 December 2019
doi: 10.3389/fpsyg.2019.02722

Working Memory Load Enhances the Attentional Capture of Low Reward History

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Attention priority of reward history, also called value-driven attentional capture (VDAC), is different from that of saliency or contingency. The magnitude of VDAC was found to be correlated with working memory capacity, but how cognitive control interacts with the attentional allocation of reward association is not clear. Here, we examined whether the distraction by learned color-reward association would change under different working memory load conditions. Participants were first trained with color-reward associations by searching a green/red circle with low/high reward. Then, during the test session, participants needed to search a unique shape while a green/red shape was either presented as a distractor or not shown at all. To manipulate the working memory load in the test, a digital memory task was integrated with the visual search task in half of the trials (memory load condition), but not in the other half (no-load condition). Consistent results were found in two experiments that the magnitude of attentional capture caused by low-value distractors was larger under memory load condition than under no-load condition, while there was no enough evidence supporting the influence of memory load on attentional capture by high-value distractors. These results suggested that working memory load, which occupied part of cognitive resources, reduced the priority of target information and might also modulate the strength of reward association holding in working memory. These findings extend the knowledge regarding the influence of working memory load on attentional capture of reward and suggest that reward-induced distraction is dynamic and could be modulated by cognitive control.

Keywords: attentional capture, reward, working memory, cognitive control, load theory

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Specialty section:
This article was submitted to Decision Neuroscience, a section of the journal Frontiers in Psychology

Received: *13 June 2019*
Accepted: *18 November 2019*
Published: *06 December 2019*

Citation:
Wu Y, Li T and Qu Z (2019) Working Memory Load Enhances the Attentional Capture of Low Reward History. Front. Psychol. 10:2722. doi: 10.3389/fpsyg.2019.02722

INTRODUCTION

Reward experience is appealing and powerful, which can guide our attention and shape our behavior. As we all know, attention plays an important role in selecting sensory input into awareness. In recent years, an increasing number of studies found that reward history can induce capture of attention (Raymond and O'Brien, 2009; Failing and Theeuwes, 2014), which has challenged the traditional view of dichotomy of attentional selection (Anderson et al., 2011b; Awh et al., 2012): one is top-down or goal-directed attentional selection, which means the stimuli that are related to current goal will get attention (Wolfe et al., 1989); the other one is bottom-up or stimulus-driven attentional capture, which means attention will be captured by a stimulus that is salient on physical properties (e.g., Theeuwes, 1992).

So, it is important to explore the cognitive basis of attentional priority of reward history and reveal the interactions between it and other cognitive processes.

The attentional priority of reward-related information was first observed in visual search tasks. First, participants need to search the target of certain colors and get rewards trial by trial in a training session. After that, in the test session, the target changes into a unique shape, and the former target color turns to be one of the distractors in some trials and no reward will be given anymore. As a result, the reaction times (RTs) of subjects get longer when the distractors that used to be associated with reward during training appeared compared to no reward-related distractor, which is called value-driven attentional capture (VDAC, Hickey et al., 2010; Anderson et al., 2011b; Awh et al., 2012; Chelazzi et al., 2013).

Value-driven attentional capture is different from goal-directed attention selection and stimulus-driven attention capture for evidence from three aspects. First, even if the color that is rewarded during training is unique among distractors, the high and low value of color make the effect of VDAC different (Anderson et al., 2011a), which means the capture is not determined by the salient color itself but by the value of reward. Second, the reward-related stimulus has no common with a current target, and its effect is context-dependent. Anderson (2015) found the effect size of VDAC depends on the situation where the association of reward value is built. Third, learning the association between a stimulus and a reward is an indispensable part of VDAC. The repeated occurrence of a target and a reward makes the brain generate a predictive signal for the target when it shows up, which modulates the priority of attention (Sali et al., 2014). Accordingly, reward history seems to attract attention in a direct and special way rather than through a goal-directed or stimulus-driven way. Although their mechanisms are different, saliency and reward can have interactions on attention. For example, Wang et al. (2013) found that VDAC was easier to appear when the reward was associated with color than with shape. However, it remains unclear how VDAC interacts with goal-directed cognitive control.

Working memory acts as an important role in goal-directed attention control (Desimone and Duncan, 1995; Baddeley, 1996). Recent studies revealed that working memory also plays an important role in VDAC. For example, Anderson et al. (2011a) found that people with lower working memory capacity exhibited stronger attentional capture by stimuli with reward history. Another eye movement study (Anderson and Yantis, 2012) further verified a negative correlation between working memory capacity and extent of VDAC. However, these studies did not manipulate the cognitive control to reveal the modulation of working memory on VDAC directly.

Working memory load will occupy cognitive resources and may influence the attentional selection in two contradictory ways. The first way is that, working memory load might impair attentional selection because the processing of distractors cannot be well inhibited by executive control. An fMRI study found that correctly allocating attention to target location needs task-related information with good priority in working memory; high working memory load will impair the priority of target and hence processing of distractor will get enhanced (De Fockert et al., 2001). Specifically, in a flanker task, the distraction is stronger under high working memory load than low working memory load (Lavie et al., 2004). Similarly, in a visual search task, memorizing digits at the same time makes performance more susceptible to irrelevant unique-color stimuli compared to no memory task condition (Lavie and De Fockert, 2005). The second way is that, working memory load might reduce distraction and facilitate allocation of attention to targets. SanMiguel et al. (2008) found that, in a visual classification task, working memory load will reduce the distraction of novel sound both behaviorally and as an index by an attenuation of the late phase of the novelty-P3 EEG signal. So, it is proposed that the effect of working memory load on distraction depends on the nature of the distraction (SanMiguel et al., 2008). Considering the priority of reward history is learning- and context-dependent, which is different from that of saliency, the influence of working memory load on VDAC is worthy to be investigated.

In the current study, we aim to reveal the modulation of working memory load on VDAC directly. Given the previously mentioned two different ways concerning the relationship between working memory and distraction, working memory load may enlarge or reduce VDAC. However, in most studies of VDAC, the reward is associated with visual stimuli that can cause response conflict in visual attention tasks, which is different from totally task-irrelevant auditory distractions used in SamMiguel's visual classification task (2008). So, here we suppose that the effect of VDAC by visual stimuli would get stronger under working memory load condition. By combining a dual-task paradigm (Pashler, 1994; Lavie and De Fockert, 2005; Muller-Gass and Schröger, 2007) with the value-learning procedure, we manipulated working memory load through a digital memory task and measured VDAC in a visual search task to test the hypothesis.

EXPERIMENT 1

Materials and Methods

Participants

Nineteen undergraduates participated in the formal experiment. One participant did not gaze at the fixation point during the experiment and was rejected from the analysis. Data of eighteen participants were analyzed (nine males and nine females). They were 17–22 years old with a mean age of 19.5 (*SD* = 1.29). All of them had normal or corrected-to-normal visual acuity and had no mental disease history. The experiment was approved by the Ethics Committee of the Department of Psychology, Sun Yat-sen University. Before the experiment, all participants signed informed consent in accordance with the Declaration of Helsinki.

Task and Stimuli

To examine the modulation of working memory on the attentional priority of reward history, two variables, working memory load (no load/load) and association between color and reward (no reward/low reward/high reward), were manipulated within subjects. During the training session, the associations were built through visual search and reward feedback trial by trial. In the test session, each participant finished both a single task (with no working memory load) and a dual task (with working memory load).

In the visual search task during the training session, six circles (each 2.3° × 2.3°) with different colors (all possible colors used in training and testing session: red, green, blue, cyan, pink, orange, yellow, white) were presented with an equal distance in an imaginary ring (10° × 10°) (**Figure 1**). Search targets were red and green circles, and only one of them would appear in each trial. In a red or green circle, there was a horizontal or vertical white bar (1.1°). In circles with other colors, the bars were 45 degrees off-axial directions. Participants were required to judge the orientation of the bar in a red or green circle as soon as possible. The reward of the current trial and total amount of reward appeared after response. There were two kinds of color-reward associations which were balanced between subjects. For half participants, red color was associated with high reward and green color was associated with low reward. For the other half participants, red color was associated with low reward while green color was associated with high reward. In each trial, if the color (red/green) associated with high reward showed up and the bar inside it was correctly responded, then the participant would receive 0.275 yuan with an 80% possibility or 0.055 yuan with a 20% possibility. If the target was the color (green/red) with low reward, then the participant would receive 0.055 yuan with an 80% possibility or 0.275 yuan with a 20% possibility.

In the visual search task during the testing session, five diamonds and one circle or five circles and one diamond composed an imaginary ring in the search display. Participants were asked to judge the orientation of the bar (horizontal or vertical) in a unique shape. Bars in other shapes were 45 degrees off-axial directions. All six shapes had different colors, and in 2/3 trials, one of the distractors was red or green. In the remaining 1/3 trials, which is the no-reward condition, all colors appeared in the training session, but none of them was associated with reward before. Participants were informed that there would be no reward in the test session and the colors were irrelevant anymore.

In working memory task during the test session, for each trial, six numbers which were randomly chosen from 1 to 9 were presented in the center of the screen. No three consecutive numbers were incrementing or decrementing, and all numbers appeared with equal probabilities. The probe number was also randomly chosen from 1 to 9. Participants were asked to report whether the probe number was among the memory array.

Procedure

Each participant was tested in a dimly lit room, sitting in front of the screen with a viewing distance of 50 cm. Before training, participants practiced for 24 trials with no reward. There were 240 trials in the training session, and 360 trials in the test session. In the test session, half trials were under single-task condition (i.e., without working memory task), and the other half were under dual-task condition (i.e., with working memory task). The two conditions were divided into two blocks separately, and the order of blocks was balanced between subjects.

In the training session, each trial began with a fixation display for 400, 500, or 600 ms randomly. Then search display appeared until response or for 800 ms. Participants were asked to press key *m* for a vertical bar or press key *z* for a horizontal bar in the target circle as soon as possible. Incorrect responses were followed by a 1000 Hz beep with 100 ms duration. After that, the feedback display showed up for 1500 ms to inform participants of the current reward and their total rewards. The inter-trial interval was 1000 ms.

In the test session, for the dual-task condition, each trial began with a fixation display (400, 500, or 600 ms duration) and then was followed by a digit array for 1500 ms. Participants were told to memorize all numbers in the array and to judge whether the probe number was one of them at the end of the trial. Then after another fixation display for 2000 ms, a search display appeared. Participants needed to press key *m* for a vertical bar or to press key *z* for a horizontal bar in the unique shape as soon as possible. After response or 1500 ms, the probe number appeared, and participants should press *a* for yes and *k* for no within 3000 ms. The inter-trial interval was 500 ms.

For the single-task condition, a search display appeared following an initial random period of fixation (400, 500, or 600 ms) and waited for response until 1200 ms. And the trial ended with an inter-trial interval of 500 ms.

Analysis

According to the appearance of reward associated colors, the trials in the test session were classified as three conditions: high reward, low reward, and no reward. Besides, based on the single-task or dual-task condition, trials in the test session were also tagged as no-load and load conditions. A within-subject repeated measures analysis of variance (ANOVA) was used to analyze RTs and error rates. All the statistical tests were conducted by using SPSS (version 22), and the statistical threshold was set at 0.05. *Post hoc* analysis was performed using Fisher's Least Square Difference (LSD) test (Milliken and Johnson, 1984).

Results

Value-Driven Attentional Capture

In the training session, RTs of high-reward and low-reward conditions were comparable [$t(17) = -0.72$, $p = 0.479$]. We divided the training session into two phases and conducted a two-way repeated measures ANOVA to reveal the training effect. A significant main effect of training was found [$F(1, 17) = 17.72$, $MS_e = 439.59$, $p = 0.001$, $\eta_p^2 = 0.51$], with shorter RTs in the second phase (527.21 ± 40.00 ms, $M \pm SD$) compared to the first phase (548.02 ± 31.48 ms). However, there was no significant reward effect [$F(1, 17) = 0.90$, $MS_e = 295.00$, $p = 0.356$, $\eta_p^2 = 0.05$] or interaction between reward and training [$F(1, 17) = 0.02$, $MS_e = 6.47$, $p = 0.882$, $\eta_p^2 = 0.00$]. So, participants responded faster with more training and two target colors had roughly equal attentional priority during training.

Reaction times and error rates of visual search task in the test session are shown in **Table 1**. A repeated measures ANOVA on RTs showed a significant memory load effect [$F(1, 17) = 89.82$, $MS_e = 8307.20$, $p < 0.001$, $\eta_p^2 = 0.84$], a significant reward effect [$F(2, 34) = 8.53$, $MS_e = 701.62$, $p = 0.001$, $\eta_p^2 = 0.33$],

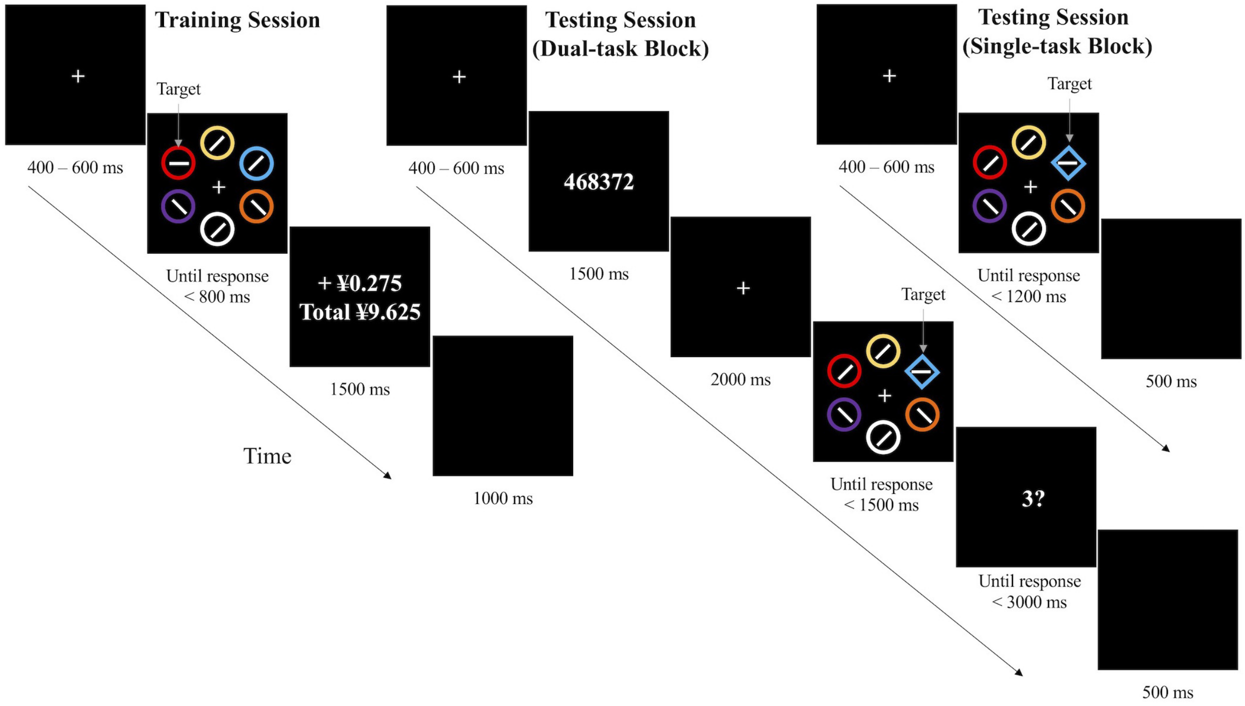

FIGURE 1 | Trial procedures of the training and test sessions.

and a significant interaction between them [$F(2, 32) = 5.63$, $MS_e = 401.80$, $p = 0.008$, $\eta_p^2 = 0.25$]. Then we analyzed the reward effects in single-task and dual-task conditions separately. Consistent with previous studies on VDAC, in the single-task condition we found a significant reward effect [$F(2, 34) = 6.22$, $MS_e = 433.78$, $p = 0.005$, $\eta_p^2 = 0.27$] and a linear trend on three reward value levels (no vs. low vs. high) [$F(1,17) = 11.43$, $MS_e = 457.22$, $p = 0.004$, $\eta_p^2 = 0.40$], which indicated that attentional capture cannot be merely explained by the selection history in training session. *Post hoc* comparisons showed significant longer RTs in low- and high-reward conditions compared to no-reward condition (Fisher's LSD: $p = 0.012$ and $p = 0.004$, respectively). As for the dual-task condition, the reward effect was also significant [$F(2, 34) = 8.28$, $MS_e = 669.64$, $p = 0.001, \eta_p^2 = 0.33$]. *Post hoc* comparisons showed significant longer RTs in low-reward condition compared to no-reward and high-reward conditions (Fisher's LSD: $p < 0.001$ and $p = 0.010$, respectively), but there was no significant RT difference between no-reward and high-reward conditions (Fisher's LSD: $p = 0.288$).

TABLE 1 | Descriptive statistics of Experiment 1 ($N = 18$).

	Reaction time (standard deviation) (in millisecond)		Error rate (standard deviation) (in percent)	
Distractor type	**No load**	**Load**	**No load**	**Load**
No reward	646.64 (88.16)	810.69 (92.47)	11.60 (5.79)	4.37 (5.10)
Low reward	662.43 (101.68)	845.10 (101.47)	11.39 (7.61)	7.84 (6.73)
High reward	670.74 (97.16)	821.89 (108.72)	13.12 (6.40)	5.81 (4.26)

A repeated measures ANOVA on error rates showed a significant main effect of working memory load [$F(1,17) = 18.51$, $MS_e = 52.94$, $p < 0.001$, $\eta_p^2 = 0.52$]. No significant main effect of reward [$F(2,34) = 29.29$, $MS_e = 18.06$, $p = 0.212$, $\eta_p^2 = 0.09$] or interaction between reward and memory load [$F(2,32) = 3.18$, $MS_e = 13.13$, $p = 0.054 < 0.01$, $\eta_p^2 = 0.16$] was found. Different with a previous study (Lavie and De Fockert, 2005), we found error rates was higher when there was no memory load compared to when there was memory load, suggesting that participants in the current experiment was more careful in the dual task. Since neither reward effect nor interaction was significant for error rates, there was no trade-off between error rates and RTs.

The Interaction Between Reward and Working Memory Load

Considering that the meaning of interaction between 2-level working memory load and 3-level reward association might be complicated and indirect, to further explain the interaction, we subtracting RTs of no-reward condition from those of low- and high-reward conditions to get two magnitudes of VDAC, and then reconducted a 2 × 2 repeated measures ANOVA with factors being load and reward (**Figure 2**, left). Results showed that the interaction between working memory load and reward was significant [$F(1,17) = 10.52$, $p = 0.005$, $\eta_p^2 = 0.38$], whereas neither the main effect of load [$F(1,17) = 0.13$, $p = 0.72$, $\eta_p^2 = 0.01$] or the main effect of reward [$F(1,17) = 1.40$, $p = 0.254$, $\eta_p^2 = 0.08$] was significant. *Post hoc* pairwise comparisons were

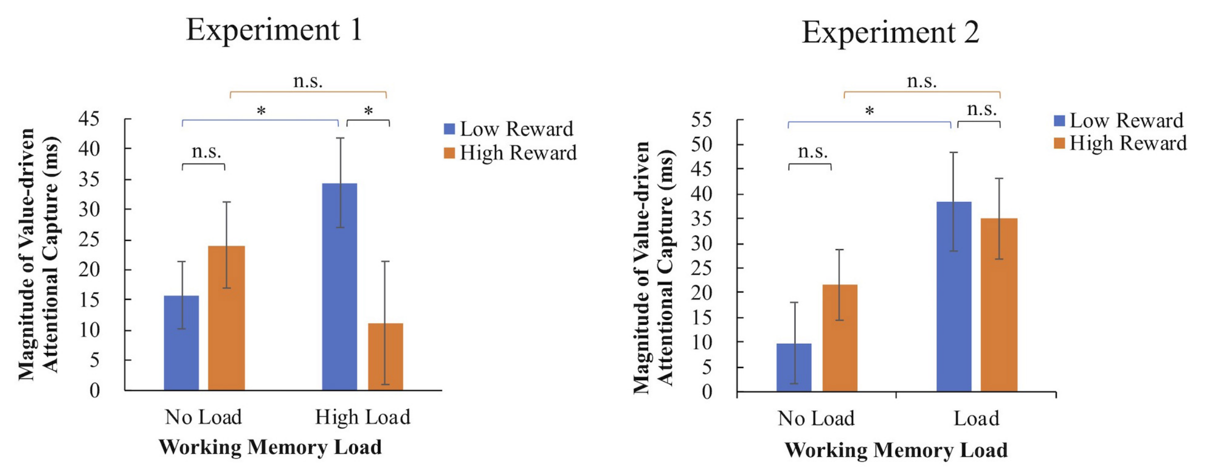

FIGURE 2 | Working memory load interacts with value-driven attention capture. Error bars represent standard error. Fisher's LSD for reaction time: $^{*}p < 0.05$, n.s., not significant.

conducted by using the least significant difference (LSD) method. Attentional capture of low reward was significantly stronger under working memory load condition than under no-load condition (Fisher's LSD: $p = 0.016$). However, attentional capture of high reward showed no significant difference between load and no-load conditions (Fisher's LSD: $p = 0.264$). These results indicated that, attentional capture driven by low reward history was strengthened in the dual-task condition while attentional capture of high reward was equivalent between single-task and dual-task conditions. Besides, under no-load condition, there was no significant difference of attentional capture between low- and high-reward conditions (Fisher's LSD: $p = 0.309$), but under load condition, attentional capture of low reward was greater than that of high reward (Fisher's LSD: $p = 0.010$).

The 2 × 2 interaction between load and reward (low vs. high reward) above could not fully explain the aforementioned 2(load) × 3(reward) interaction. Considering the data patterns shown in **Table 1**, it would be helpful to do another 2 × 2 repeated measures ANOVA on no-reward and low-reward conditions (Cohen, 2008). We found a significant interaction between load and reward (no reward vs. low reward) [$F(1,17) = 7.18$, $MS_e = 217.41$, $p = 0.016$, $\eta_p^2 = 0.30$], which indicated a steeper increase of RTs with memory load for low-reward condition compared to no-reward condition.

In the digit memory task, a repeated measures ANOVA showed no significant main effect of reward [$F(2,34) = 0.20$, $MS_e = 0.001$, $p = 0.818$, $\eta_p^2 = 0.01$] on memory accuracies (92.4, 92.5, and 91.9% in no-reward, low-reward, and high-reward conditions, respectively), meaning that attentional capture by reward association did not impair the performance of memory task.

EXPERIMENT 2

In Experiment 1, we found greater attentional capture driven by low reward history under working memory load, while no significant change of attentional capture caused by high-reward association was observed between load and no-load conditions. One might argue that, in the training or test session, participants might sometimes search for a horizontal or vertical bar instead of specific colors or shapes. To reduce this confounding factor and to verify the results in Experiment 1, we changed all orientations of bars in distractors into axial directions in Experiment 2.

Participants

Nineteen undergraduates participated in Experiment 2. One participant's performance in the training session was poor (accuracy = 0.66), which might lead to insufficient trials to learn the association between color and reward. So, the data of this participant was excluded from further analysis. Eighteen participants (6 males and 12 females) were 18–23 years old, with a mean age of 19.94 years old ($SD = 1.35$). All of them had normal or corrected-to-normal visual acuity and had no mental disease history. The experiment was approved by the Ethics Committee of the Department of Psychology, Sun Yat-sen University. Before the experiment, each participant signed informed consent in accordance with the Declaration of Helsinki.

Materials and Methods

The design, procedure, and most of the stimuli of Experiment 2 were the same as Experiment 1. The only difference was that the bar orientations inside distractors were horizontal or vertical in both the training and test sessions.

Results

Value-Driven Attentional Capture

To ensure the training effect of reward associations, we divided the training session into two phases as in Experiment 1and did a repeated measures ANOVA on RTs. Similar to the results of Experiment 1, we found a significant main effect of training [$F(1, 17) = 7.91$, $MS_e = 421.293$, $p = 0.012$, $\eta_p^2 = 0.32$], but no significant effect of reward [$F(1, 17) = 1.27$, $MS_e = 370.26$,

$p = 0.28$, $\eta_p^2 = 0.07$]. Different from Experiment 1, a significant interaction between training phase and reward [$F(1, 17) = 5.627$, $MS_e = 146.13$, $p = 0.03$, $\eta_p^2 = 0.25$] was found, which resulted from a greater RT decrease with training for the high-reward condition (first phase: 563.52 ± 28.42 ms; second phase: 543.16 ± 29.83 ms) compared to the low-reward condition (first phase: 561.88 ± 31.18 ms; second phase: 555.03 ± 35.98 ms).

RTs and error rates of visual search task in the test session are shown in **Table 2**. A repeated measures ANOVA on RTs showed a significant load effect [$F(1,17) = 97.64$, $MS_e = 3791.33$, $p < 0.001$, $\eta_p^2 = 0.85$], a significant reward effect [$F(2,34) = 13.13$, $MS_e = 639.96$, $p < 0.001$, $\eta_p^2 = 0.44$], and a marginally significant interaction between them [$F(2,32) = 2.77$, $MS_e = 662.64$, $p = 0.077$, $\eta_p^2 = 0.14$]. Reward effects were significant under both no-load condition [$F(2,34) = 4.00$, $MS_e = 526.21$, $p = 0.028$, $\eta_p^2 = 0.19$] and load condition [$F(2,34) = 10.48$, $MS_e = 776.39$, $p < 0.001$, $\eta_p^2 = 0.38$]. In single visual search task (no-load condition), consistent with previous studies on VDAC and Experiment 1, we also found a significant linear trend of RTs under three value levels (no vs. low vs. high) [$F(1,17) = 9.15$, $MS_e = 4199.89$, $p = 0.008$, $\eta_p^2 = 0.35$]. *Post hoc* comparisons showed longer RTs under high-reward condition compared to no-reward condition (Fisher's LSD: $p = 0.008$) and there was no significant difference between no-reward and low-reward conditions (Fisher's LSD: $p = 0.247$) or between low- and high-reward conditions (Fisher's LSD: $p = 0.138$). So, for no working memory load condition, both experiments indicated a linear increment of attentional capture with increased value of reward. As for load condition, *post hoc* comparisons showed significant longer RTs under low- and high-reward conditions compared to no-reward condition (Fisher's LSD: $p = 0.001$ and $p < 0.001$, respectively), but no significant difference was found between low- and high-reward conditions (Fisher's LSD: $p = 0.725$).

A repeated measures ANOVA on error rates showed no significant main effect of reward [$F(2, 34) = 2.28$, $MS_e = 27.62$, $p = 0.118$, $\eta_p^2 = 0.12$], no significant main effect of working memory load [$F(1, 17) = 0.93$, $MS_e = 70.46$, $p = 0.349$, $\eta_p^2 = 0.05$], and no significant interaction [$F(2, 34) = 1.16$, $MS_e = 22.42$, $p = 0.326$, $\eta_p^2 = 0.06$]. So, there was no trade-off between RTs and error rates.

The Interaction Between Reward and Working Memory Load

As in Experiment 1, we also calculated the magnitude of attentional capture by subtracting RTs of no-reward condition from those of low- and high-reward conditions and did a 2 × 2 repeated measures ANOVA (**Figure 2**, right). The main effect of load is marginally significant [$F(1, 17) = 3.99$, $MS_e = 1984.05$, $p = 0.062$, $\eta_p^2 = 0.19$], but there was no significant main effect of reward [$F(1, 17) = 0.455$, $MS_e = 682.78$, $p = 0.509$, $\eta_p^2 = 0.03$] or significant interaction [$F(1, 17) = 10.52$, $MS_e = 663.92$, $p = 0.228$, $\eta_p^2 = 0.08$]. Although the interaction between reward and working memory load was not significant, which is different with Experiment 1, we ran *post hoc* comparisons to make sure that this inconsistency resulted from the high-reward condition. *Post hoc* pairwise comparisons were conducted by using the LSD method. Consistent with findings in Experiment 1, attentional capture of low reward was significantly stronger under working memory load than under no-load condition (Fisher's LSD: $p = 0.022$), whereas attentional capture of high reward showed no significant difference between load and no-load conditions (Fisher's LSD: $p = 0.313$). Meantime, no significant difference of attentional capture was found between low and high rewards under either load or no-load condition (Fisher's LSD: $p = 0.725$ and $p = 0.138$, respectively). Compared with the results in Experiment 1, the difference of interaction between the two experiments appeared to stem from the different patterns in high-reward condition.

TABLE 2 | Descriptive statistics of Experiment 2 ($N = 18$).

Distractor type	Reaction time (standard deviation) (in millisecond)		Error rate (standard deviation) (in percent)	
	No load	Load	No load	Load
No reward	807.99 (92.43)	911.10 (89.62)	15.45 (7.02)	14.46 (6.22)
Low reward	817.84 (101.38)	949.52 (92.46)	17.60 (8.36)	16.29 (7.22)
High reward	829.59 (103.74)	946.08 (89.14)	18.14 (7.54)	14.78 (7.01)

To better explain the marginally significant 2 × 3 interaction and data patterns in **Table 2**, we also did a 2 × 2 repeated measures ANOVA on load and reward (no reward vs. low reward) as in Experiment 1. Again, a significant interaction was found [$F(1,17) = 6.36$, $MS_e = 577.40$, $p = 0.022$, $\eta_p^2 = 0.27$], which indicated a steeper RT increase with memory load for low-reward condition compared to no-reward condition. So, combining the results of two separate ANOVAs, the interaction between load and reward could be accounted for by enhanced attentional capture of low reward under working memory load.

DISCUSSION

Reward history can guide and attract our attention no matter what our current goal is. It is especially essential to know how attention is allocated when people are under a load of a dual task. Under certain conditions, working memory load can improve (SanMiguel et al., 2008) or impair (De Fockert et al., 2001; Lavie and De Fockert, 2005) attentional selection. The current study focused on the interaction between working memory load and VDAC. Both experiments revealed that working memory load enhanced the attentional capture of low reward history but had mild or no effect on the capture of high reward history. Our results suggest that working memory load may not only impair the maintenance of target information but also modulate learned color-reward association.

Mechanism of Working Memory Load on Value-Driven Attentional Capture

One robust finding in both Experiment 1 and 2 is the enlargement of attentional capture of low reward history under memory load condition relative to no-load condition, which is consistent with what load theory predicts. According to the load theory (Lavie et al., 2004), when the task is relatively easy and perceptual load is low, the remaining cognitive sources will be distributed to irrelevant distractors, and attention is in charge of eliminating them. The efficiency of the elimination process is influenced by working memory (Lavie et al., 2004), and higher working memory load would cause stronger distraction (Muller-Gass and Schröger, 2007; Lavie, 2010). For example, in a visual search task where participants needed to find a unique shape while a unique color appeared as a distractor, memorizing digits at the same time made RTs much longer than no memory task condition (Lavie and De Fockert, 2005). Working memory load will enhance the processing of distractor (De Fockert et al., 2001), which can even improve the processing of a low-contrast Gabor stimulus in the presence of collinear flanking Gabors (De Fockert and Leiser, 2014). In our study, working memory load may hamper the inhibition of learned color-reward association, which enlarged the extent of attentional capture of reward and therefore prolonged the RT to find the target.

Another possible mechanism of memory load effect on attention is that the distribution of attention is dispersive at the beginning of each trial (Eriksen and James, 1986), and it is hard to get focus due to working memory load and insufficient resources (Ahmed and De Fockert, 2012a). Ahmed and De Fockert (2012b) found improved performance during attention to a global level under working memory load. The spread of attention caused by working memory load can even reduce the inattentional blindness (De Fockert and Bremner, 2011).

In Experiment 1, the attentional capture of low reward history was greater than that of high reward history under working memory load condition. To further examine this finding, we considered a possible reason and designed Experiment 2 to test it. We speculated that in Experiment 1, the window of attention could be large and dispersive, and hence participants might in some trials search for the horizontal or vertical bars by only attending their orientations while ignoring the colors or shapes, which made the color-reward associations hard to be built and therefore less capable of capturing attention. In Experiment 2, we made color/shape the only feature defining the target in the training/test session by changing all distracting bars into axial directions (vertical or horizontal). Different from the result of more attentional capture of low reward than high reward under load condition in Experiment 1, in Experiment 2, no significant difference of attentional capture was found between low- and high-reward conditions under load condition. This inconsistent patterns between experiments indicated that high-reward association in Experiment 2 exhibited higher attentional priority compared to Experiment 1, supporting that the manipulation of changing orientations of distractors is an efficient way to strengthen reward associations. Another difference between the two experiments was the training effect of reward association. In the training session of Experiment 1, there was no direct evidence supporting that low and high rewards improved visual search performance in different degrees. However, in the training session of Experiment 2, we found a greater decrease of RT for high-reward condition compared to low-reward condition, which indicated a better training effect of color-reward associations in Experiment 2 than in Experiment 1. Taken together, the inconsistent data patterns of low and high rewards under load condition in two experiments might be due to different strengths of the high-reward association in two experiments. This also implies that association strength during training is a key experimental factor to induce an attentional capture of reward and should be taken carefully.

As for why the load effect on high reward attentional capture is not significant in both Experiment 1 and 2, there might be three possible reasons. The first is the training of reward association might be not enough, which made both attentional capture by reward history and memory load effect hard to be observed. For example, the training session might be a little short, or the associations between reward and color in the training session are relatively weak. Actually, in Experiment 1, participants could finish the training session quite well even when ignoring the colors of shapes. After changing the association strength by making color (red and green) the only feature bound with the target (or reward) in training session in Experiment 2, the mean magnitude of attentional capture by high reward increased with load numerically (although not significant). The second speculation is that attentional capture of high reward already reached the ceiling, which cannot be further enlarged by working memory load. In Experiment 2, attentional capture of both low and high rewards increased with load numerically, and besides, under the load condition, attentional capture of low and high rewards reached a same level. So the results can be a combination of load effect and ceiling effect. Finally, there is a third possibility that working memory load may impair the high-reward association with color held in working memory more than low-reward association, which is a counterforce to capture enlargement caused by less inhibition. Although there is no direct evidence supporting this hypothesis, as we will discuss in the next session in detail, there do exist some findings indicating that working memory load can interfere with reward association stored in memory space.

Working Memory and Reward Association

In the present study, we did not find a significant difference in attentional capture of high reward between no-load and load conditions. This may be because the reward association is held in working memory, and working memory load may constrain or even impair this information, which makes the facilitation of reward association on distractor processing constant or even reduced. Infanti et al. (2015) found learned feature-reward associations would interfere with mnemonic representations during encoding and holding periods of working memory when no reward was provided. This indicates that reward associations learned through training can be easily invoked by working memory and interact with contents in working memory when the reward-related feature appears. So, it is reasonable that in current experiments, when red and green colors appeared in the test session, the color-reward associations were invoked, and the priority of target information was hampered, leading to attentional distraction. As for load condition, working memory load would occupy memory space, which might interfere with the color-reward association that also stored in memory space.

Therefore, the final consequence depended on the level of reward association remained in memory space.

Besides, Gong and Li (2014) found working memory performance was improved when the items were in the high reward-associated color than those in the low reward-associated or non-rewarded color. Their results also showed interaction between reward association and working memory contents. Different from Gong and Li 's (2014) study which focused on how the reward association influences working memory, our study addressed how working memory modulates attention allocation with reward association and added some new information to this field.

In the current study, we used no memory load rather than low memory load to shorten the duration of test session, which could avoid possible attenuation of learned reward associations along with time. A similar design (no load vs. high load) was also adopted in a previous attentional capture study (Lavie and De Fockert, 2005; Experiment 1). A limitation of such designs is that the difference between no-load condition and high-load condition would inevitably include task switching in addition to memory load, which makes task switching a potential confounding factor. Future studies are needed to investigate whether task switching and memory load have different influence on attentional distraction of reward history.

In summary, consistent results were found in two experiments that attentional capture of low-reward association was enhanced under memory load condition relative to no-load condition, while no significant memory load effect was found in attentional capture of high-reward association. We propose that working memory load, which occupies part of cognitive resources, hampers the priority of target information during the process of attentional selection. Our findings extend the knowledge of the influence of working memory load on attentional capture of reward, suggesting that attentional distraction caused by reward association is dynamic and could be modulated by cognitive control.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation, to any qualified researcher.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Ethics Committee of the Department of Psychology, Sun Yat-sen University. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

AUTHOR CONTRIBUTIONS

YW and ZQ designed the research. YW performed the research and analyzed the data. YW, TL, and ZQ wrote the manuscript.

FUNDING

This study was supported by grants from the National Nature Science Foundation of China (31271190) and the Humanities and Social Science Fund of Ministry of Education of China (19YJA190004).

REFERENCES

Ahmed, L., and De Fockert, J. W. (2012a). Focusing on attention: the effects of working memory capacity and load on selective attention. *PLoS One* 7:e4310. doi: 10.1371/journal.pone.0043101

Ahmed, L., and De Fockert, J. W. (2012b). Working memory load can both improve and impair selective attention: evidence from the navon paradigm. *Atten. Percept. Psychophys.* 74, 1397–1405. doi: 10.3758/s13414-012-0357-1

Anderson, B. A. (2015). Value-driven attentional priority is context specific. *Psychon. Bull. Rev.* 22, 750–756. doi: 10.3758/s13423-014-0724-0

Anderson, B. A., Laurent, P. A., and Yantis, S. (2011a). Learned value magnifies salience-based attentional capture. *PLoS One* 6:e27926. doi: 10.1371/journal.pone.0027926

Anderson, B. A., Laurent, P. A., and Yantis, S. (2011b). Value-driven attentional capture. *Proc. Natl. Acad. Sci. U.S.A.* 108, 10367–10371. doi: 10.1073/pnas.1104047108

Anderson, B. A., and Yantis, S. (2012). Value-driven attentional and oculomotor capture during goal-directed, unconstrained viewing. *Atten. Percept. Psychophys.* 74, 1644–1653. doi: 10.3758/s13414-012-0348-2

Awh, E., Belopolsky, A. V., and Theeuwes, J. (2012). Top-down versus bottom-up attentional control: a failed theoretical dichotomy. *Trends Cogn. Sci.* 16, 437–443. doi: 10.1016/j.tics.2012.06.010

Baddeley, A. (1996). The fractionation of working memory. *Proc. Natl. Acad. Sci. U.S.A.* 93, 13468–13472. doi: 10.1073/pnas.93.24.13468

Chelazzi, L., Perlato, A., Santandrea, E., and Della Libera, C. (2013). Rewards teach visual selective attention. *Vis. Res.* 85, 58–72. doi: 10.1016/j.visres.2012.12.005

Cohen, B. H. (2008). *Explaining Psychological Statistics*. Hoboken, NJ: John Wiley & Sons.

De Fockert, J. W., and Bremner, A. J. (2011). Release of inattentional blindness by high working memory load: elucidating the relationship between working memory and selective attention. *Cognition* 121, 400–408. doi: 10.1016/j.cognition.2011.08.01632

De Fockert, J. W., and Leiser, J. (2014). Better target detection in the presence of collinear flankers under high working memory load. *Front. Hum. Neurosci.* 8:821. doi: 10.3389/fnhum.2014.00821

De Fockert, J. W., Rees, G., Frith, C. D., and Lavie, N. (2001). The role of working memory in visual selective attention. *Science* 291, 1803–1806. doi: 10.1126/science.1056496

Desimone, R., and Duncan, J. (1995). Neural mechanisms of selective visual attention. *Annu. Rev. Neurosci.* 18, 193–222. doi: 10.1146/annurev.ne.18.030195.001205

Eriksen, C. W., and James, J. D. S. (1986). Visual attention within and around the field of focal attention: a zoom lens model. *Percept. Psychophys.* 40, 225–240. doi: 10.3758/BF03211502

Failing, M. F., and Theeuwes, J. (2014). Exogenous visual orienting by reward. *J. Vis.* 14, 6–6. doi: 10.1167/14.5.6

Gong, M., and Li, S. (2014). Learned reward association improves visual working memory. *J. Exp. Psychol. Hum. Percept. Perform.* 40, 841–856. doi: 10.1037/a0035131

Hickey, C., Chelazzi, L., and Theeuwes, J. (2010). Reward guides vision when it's your thing: trait reward-seeking in reward-mediated visual priming. *PLoS One* 5:e14087. doi: 10.1371/journal.pone.0014087

Infanti, E., Hickey, C., and Turatto, M. (2015). Reward associations impact both iconic and visual working memory. *Vis. Res.* 107, 22–29. doi: 10.1016/j.visres.2014.11.008

Lavie, N. (2010). Attention, distraction, and cognitive control under load. *Curr. Dir. Psychol. Sci.* 19, 143–148. doi: 10.1177/0963721410370295

Lavie, N., and De Fockert, J. (2005). The role of working memory in attentional capture. *Psychon. Bull. Rev.* 12, 669–674. doi: 10.3758/BF03196756

Lavie, N., Hirst, A., De Fockert, J. W., and Viding, E. (2004). Load theory of selective attention and cognitive control. *J. Exp. Psychol. Gen.* 133:339. doi: 10.1037/0096-3445.133.3.339

Milliken, G. A., and Johnson, D. E. (1984). *Analysis of Messy Data, Volume I: Designed Experiments*. Belmont, CA: Wadsworth. Inc.

Muller-Gass, A., and Schröger, E. (2007). Perceptual and cognitive task difficulty has differential effects on auditory distraction. *Brain Res.* 1136, 169–177. doi: 10.1016/j.brainres.2006.12.020

Pashler, H. (1994). Dual-task interference in simple tasks: data and theory. *Psychol. Bull.* 116, 220–244. doi: 10.1037/0033-2909.116.2.220

Raymond, J. E., and O'Brien, J. L. (2009). Selective visual attention and motivation the consequences of value learning in an attentional blink task. *Psychol. Sci.* 20, 981–988. doi: 10.1111/j.1467-9280.2009.02391.x

Sali, A. W., Anderson, B. A., and Yantis, S. (2014). The role of reward prediction in the control of attention. *J. Exp. Psychol. Hum. Percept. Perform.* 40, 1654–1664. doi: 10.1037/a0037267

SanMiguel, I., Corral, M. J., and Escera, C. (2008). When loading working memory reduces distraction: behavioral and electrophysiological evidence from an auditory-visual distraction paradigm. *J. Cogn. Neurosci.* 20, 1131–1145. doi: 10.1162/jocn.2008.20078

Theeuwes, J. (1992). Perceptual selectivity for color and form. *Percept. Psychophys.* 51, 599–606. doi: 10.3758/BF03211656

Wang, L., Yu, H., and Zhou, X. (2013). Interaction between value and perceptual salience in value-driven attentional. *J. Vis.* 13, 5. doi: 10.1167/13.3.5

Wolfe, J. M., Cave, K. R., and Franzel, S. L. (1989). Guided search: an alternative to the feature integration model for visual search. *J. Exp. Psychol. Hum. Percept. Perform.* 15, 419–433. doi: 10.1037//0096-1523.15.3.419

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers
in Neuroscience

ORIGINAL RESEARCH
published: 13 December 2019
doi: 10.3389/fnins.2019.01319

The Impact of Callous-Unemotional Traits and Externalizing Tendencies on Neural Responsivity to Reward and Punishment in Healthy Adolescents

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Specialty section:
This article was submitted to
Decision Neuroscience,
a section of the journal
Frontiers in Neuroscience

Received: *14 July 2019*
Accepted: *25 November 2019*
Published: *13 December 2019*

Citation:
Huang Y, Wu T, Gao Y, Luo Y, Wu Z, Fagan S, Leung S and Li X (2019) The Impact of Callous-Unemotional Traits and Externalizing Tendencies on Neural Responsivity to Reward and Punishment in Healthy Adolescents.
Front. Neurosci. 13:1319.
doi: 10.3389/fnins.2019.01319

Both externalizing behavior and callous-unemotional (CU) traits in youth are precursors to later criminal offending in adulthood. It is posited that disruptions in reward and punishment processes may engender problematic behavior, such that CU traits and externalizing behavior may be linked to a dominant reward response style (e.g., heightened responsivity to rewards) and deficient punishment-processing. However, prior research has generated mixed findings and work examining both the sole and joint contribution of CU traits and externalizing problems related to functional brain alterations is lacking. In this pilot functional magnetic resonance imaging study, we measured externalizing behavior and CU traits in a community sample of adolescents (n = 29) and examined their impacts on brain activity associated with anticipation and receipt of reward and punishment using the Modified Monetary Incentive Delay task. We found that CU traits were associated with greater activation of the ventral striatum (VST) during reward anticipation. However, this effect became non-significant after controlling for externalizing behavior, indicating substantial overlap between the CU and externalizing measures in explaining VST activation when anticipating reward. In addition, externalizing behavior (but not CU) was significantly negatively associated with amygdala activation during punishment receipt, even after controlling for CU traits. The present findings extend previous evidence of hyper-responsivity to reward and hypo-responsivity to punishment in relation to psychopathic traits and antisocial behavior to non-clinical, non-incarcerated youths.

Keywords: callous-unemotional, externalizing, reward, punishment, adolescence

INTRODUCTION

Early life presence of externalizing behavior and psychopathy are considered to be precursors to juvenile delinquency and later criminal offending. In adults, psychopathic traits are a constellation of personality characteristics comprised of callousness, lack of empathy, superficiality, and impulsivity (Hare, 2003). Research has extended the concept of psychopathy to youth by identifying the core traits (lack of empathy and/or guilt, shallow and limited affect), which are referred to as callous-unemotional (CU) traits (Frick, 1995; Barry et al., 2000; Frick et al., 2014). Externalizing behavior, including aggressive and rule-breaking behaviors, are behaviors that violate societal norms and infringe on others' rights (Liu, 2004; Calkins and Keane, 2009). The terms "externalizing behavior" and "antisocial behavior" have been used interchangeably by some researchers, although others argue that "externalizing behavior" should be reserved to characterize destructive behaviors exhibited by youth that are less severe than antisocial behaviors such as negative, hostile, and defiant acts (Shaw and Winslow, 1997; Liu, 2004). Externalizing behavior and CU traits are highly correlated (e.g., Charles et al., 2012; Pihet et al., 2015). Furthermore, the presence of CU traits in youth is associated with more severe externalizing behavior (e.g., conduct problems, delinquency, aggression) (see Frick and Dickens, 2006 for a review), and is especially useful for predicting a subgroup of individuals with antisocial behavior that are more serious and chronic in nature (Frick and White, 2008). In fact, the Diagnostic and Statistical Manual of Mental Disorders (DSM-5; American Psychiatric Association [APA], 2013) includes a CU specifier as a feature of conduct disorder [a disorder in youth characterized by externalizing behavior that tends to precede antisocial personality disorder (ASPD)]. ASPD is a personality disorder marked by persistent disregard and/or violation of other's rights, and is often accompanied by criminal and aggressive behavior (American Psychiatric Association [APA], 2013). While only 5% of youth exhibit a pervasive and egregious pattern of both CU traits and externalizing/antisocial behavior, by adulthood this 5% accounts for a staggering 50% of crime in the United States alone (Loeber et al., 2000; Hinshaw and Lee, 2003). Therefore, it is essential to understand the etiology of CU traits and externalizing behavior in youths to help combat the future development of maladaptive behaviors.

One potential etiological pathway that engenders externalizing behavior is hyperactivity to rewards and/or hypoactivity to punishment (Frick and Marsee, 2006; Pardini, 2006; Byrd et al., 2014). Specifically, reward oversensitivity in externalizing youth can result in persistent reward-seeking behavior (Quay, 1993), and antisocial youth may rely more heavily on acting on appetitive drives than evading punishment (O'Brien and Frick, 1996). Meanwhile, insensitivity to punishment has also been implicated in psychopathy and antisocial behavior (Dadds and Salmon, 2003; Hawes and Dadds, 2005). Deficits in punishment processing may result in failure to adopt appropriate behavior via passive avoidance learning (Newman and Kosson, 1986; von Borries et al., 2010), whereby externalizing/antisocial behavior may be the behavioral manifestation of punishment insensitivity (Lykken, 1995). Impaired punishment processing (i.e., hypo-responsivity) may lead to lower levels of anxiety and fear anticipation, thereby giving rise to psychopathic and antisocial tendencies. One conceptualization has postulated that psychopathy and externalizing/antisocial behavior may arise from deficits in the modulation of both reward and punishment systems (Patterson and Newman, 1993; Wallace and Newman, 2008; Byrd et al., 2014).

Processing of reward can be distinguished by two phases: anticipation of a reward and its delivery (Knutson et al., 2001b). Evidence from functional magnetic resonance imaging (fMRI) studies on healthy populations has suggested that similar regions are activated during reward anticipation and receipt (e.g., insula, dorsal and ventral striatum) (Silverman et al., 2015), with the ventral striatum (VST) being critically implicated during the processing of reward (Knutson et al., 2001b; Oldham et al., 2018). Similarly, an anticipatory phase and the delivery of the punishment are also included in the processing of punishment (Delgado et al., 2009): anticipation elicits activation of the VST, amygdala, thalamus, and insula (Oldham et al., 2018), while punishment receipt activates the anterior cingulate cortex (ACC), insula, thalamus, and orbitofrontal cortex (OFC) (Wrase et al., 2007). One recent study indicates that overlapping neural substrates, including VST, thalamus, and amygdala are implicated in both reward and punishment anticipation (Oldham et al., 2018). Taken together, anticipation and receipts of rewards and punishments may implicate brain regions that are largely overlapping, but also distinctive.

Altered function in many of these regions has been linked to reward and punishment processing deficits seen in antisocial and psychopathic adults (Hyde et al., 2013). Meanwhile, hyposensitivity to punishment and/or hypersensitivity to reward have largely been implicated in the development of externalizing behavior and CU traits in youths (Matthys et al., 2004; Rubia et al., 2009; Bjork et al., 2010), although abnormalities in various regions have been reported. For example, in one study, adolescent males with early onset conduct disorder showed decreased activation of the OFC during reward receipt (Rubia et al., 2009). In another study, adolescents diagnosed with either oppositional defiant disorder (ODD), attention deficit hyperactivity disorder (ADHD), or conduct disorder (CD) exhibited greater activation in nucleus accumbens (NAcc; considered to be a primary subregion of the VST) and the ACC in response to reward receipt (Bjork et al., 2010) when compared to healthy controls. In contrast, an investigation on 16- to 19- year-old adolescents with disruptive behavioral disorders (DBD) had compared DBD persisters (who showed early onset and persisted into late adolescence/adulthood), DBD desisters (who showed late onset and eventually ceased disruptive behaviors) and healthy controls (Cohn et al., 2015). They found that the DBD persisters showed blunted activation in the VST, but increased activation in the amygdala, to the receipt of the monetary gain, as compared to the other two groups. In addition, CU traits were associated with reduced amygdala activation in response to monetary receipt (Cohn et al., 2015). Finally, in boys aged 8- to 11- years with clinically significant conduct problems, no significant association was found between CU traits and neural response to reward receipt in any of the above regions (Byrd et al., 2018). Overall, most of the research on youth samples support the proposition that CU traits and externalizing tendencies are associated with hyper-responsivity to reward, although more work is warranted to address prior mixed findings.

In regards to punishment, several studies have found impaired aversive conditioning in psychopathic, CU, and externalizing populations, which is consistent with the punishment hypo-responsivity theory. Yet, studies have also yielded conflicting results and few have looked at both CU traits and externalizing behavior together. Youth with externalizing behavior (Gao et al., 2009, 2010b), conduct disorder (Fairchild et al., 2008), and those with CU traits from the community (Fung et al., 2005) have lower skin conductance responses (SCRs), an index of autonomic arousal, to cues that signaled punishment, indicating their lack of fear for impending punishments or risks. Studies that examined responses to the receipt of punishment have yielded comparable results to those of impending punishment. Youth with DBD showed reduced eye-blink startle responses (van Goozen et al., 2004) and reduced SCRs to uncued aversive tones (Herpertz et al., 2003) than normal controls. In youth with DBD and CU traits, reduced amygdala activation in response to punishment has been reported (Finger et al., 2011), but failed to replicate in another study (Byrd et al., 2018). However, Byrd et al. (2018) did not find any association between conduct problems and reductions in amygdala activation following punishment. In contrast, Cohn et al. (2015) found that DBD persisters had increased amygdala activation to punishment feedback.

Although not specifically related to reward and punishment, there is burgeoning evidence for an interactive role of CU traits in relation to brain deficits in externalizing adolescents. CU traits in youth with disruptive behavior have been associated with atypical brain functioning, particularly reduced amygdala response to socio-affective cues (e.g., fearful expressions) (Marsh et al., 2008; Jones et al., 2009; Viding et al., 2012; White et al., 2012), which in turn may lead to increases in proactive, goal-directed, aggressive behavior observed in youths with CU traits (Lozier et al., 2014). Alternatively, youths with behavioral problems and unspecified CU traits exhibit elevated activation in the amygdala, insula, and striatum in response to socio-affective stimuli (Herpertz et al., 2008; Passamonti et al., 2010). Research has shown that while CU traits are positively correlated with externalizing behavioral problems, these variables are, respectively, negatively and positively correlated with amygdala responses to socio-affective stimuli (Lozier et al., 2014). Moreover, externalizing boys with high CU traits exhibited amygdala hypo-reactivity to fearful faces, whereas externalizing boys with low CU traits were hyper-reactive (Viding et al., 2012). A more recent study reported similar results: youth with high CU traits showed amygdala hypo-reactivity when making judgments about causing fear in others and CU traits moderated the relationship between externalizing behavior and both the functional connectivity and activity of the amygdala (Cardinale et al., 2018). CU traits were also found to account for structural abnormalities in the amygdala of children with externalizing problems (Cardinale et al., 2019). While preliminary, these results suggest that CU traits and externalizing symptoms may play an interactive role in predicting brain deficits in youths.

In this pilot study, we aimed to extend the prior findings to non-clinical, non-incarcerated adolescents. Not only are non-clinical, non-incarcerated youth underexplored, but further examination of this group is important in identifying potential risk factors for the development of externalizing behavior and CU traits. Externalizing behavior (via the Child Behavior Checklist, CBCL; Achenbach, 1991) and CU traits (via the Inventory of Callous Unemotional Traits, ICU; Frick, 2004) were assessed in a group of adolescents from the community. They completed a modified Monetary Incentive Delay task (MID; Knutson et al., 2001a), in which participants were shown three types of geometric cues, each associated with either potential gain, loss, or no gain or loss (neutral). Their brain activation during anticipation and receipt of monetary gain and loss were acquired. Studies on healthy adolescents and adults have shown involvement of the NAcc, caudate, putamen, thalamus, and insula during the reward and loss anticipation phases of the MID (Cho et al., 2013). We expected to see hyper-responsivity to reward and hypo-responsivity to punishment in relation to externalizing and/or CU tendencies. Given that the presence of CU traits may designate a subgroup of youth with more severe externalizing tendencies (Frick and White, 2008), our second aim was to test if CU traits would interact with externalizing behavior in predicting brain activation in response to reward and punishment. It was hypothesized that adolescents with higher levels of both would show the most aberrant neural responses (e.g., hyper-responsivity to reward and hypo-responsivity to punishment).

In addition, given that prior studies have reported high correlations between externalizing behavior and CU traits (Charles et al., 2012; Pihet et al., 2015) and that they share similar etiological profiles (Frick and Dickens, 2006), we investigated the unique contribution of CU traits and externalizing behavior to reward/punishment processing in this pilot study. We predicted that there would be a great amount of overlap between externalizing behavior and CU traits in explaining brain activation. Finally, since prior research has implicated low IQ and high social adversity in antisocial behavior (e.g., Moffitt et al., 1981; Fagan et al., 2017), we included measures of IQ and social adversity as covariates. Sex and pubertal status were also included as covariates given that sex differences in the structural and functional abnormality have been found in antisocial populations (e.g., Raine et al., 2011; Visser et al., 2013) and an increasing number of studies have illustrated the effects of puberty on brain structure (Urošević et al., 2014; Herting and Sowell, 2017). To the authors' knowledge, this is the first study to investigate an interaction effect of CU traits and externalizing behavior in relation to reward and punishment processing deficits in youths.

MATERIALS AND METHODS

Participants

Data were collected as part of the Healthy Childhood Study (HCS), an ongoing longitudinal study that follows healthy children through development. Participants and their families were originally recruited from the metropolitan Brooklyn, New York community when children were 7- to 10- years old. The original cohort consisted of 340 participants [48.2% male, mean age = 9.06, standard deviation (SD) = 0.60] and their main caregivers. Youth participants with any history of drug use, psychiatric disorders, intellectual disabilities, or developmental disorders were excluded from recruitment. More details of the full cohort can be found in Gao and Zhang (2016).

From the original cohort, 32 adolescents were randomly selected and invited to participate in the current fMRI study when they were 11- to 14-year-old. Three were excluded due to excessive head motion (>8 mm in translation or >5° in rotation) during the task. The remaining 29 adolescents were comprised of 15 girls and 14 boys (mean age = 12.3, *SD* = 0.8). Twenty-three of them were right-handed. The ethnic breakdown was as follows: 58.6% Black, 24.1% Hispanic, 13.8% Caucasian, and 3.4% mixed-race/other. Caregiver participants consisted of biological mothers (86.2%) and biological fathers (13.8%).

Participants and their main caregivers were invited to the Translational and Molecular Imaging Institute of Icahn School of Medicine at Mount Sinai (ISMMS) in New York for the interview assessments, the mock scan, and the actual scan, which lasted approximately 2 h in total. Participating families were financially compensated $150 for their participation. All procedures were approved by the Institutional Review Boards of the City University of New York and the ISMMS. Written informed parental consent and youth assent were obtained from each family before participation. After consenting, caregivers filled out the CBCL and ICU. Youths filled out the ICU and Self-Rating Scale for Pubertal Development (see below) after the brain scan.

Measures

Externalizing Problems

Externalizing behavior was measured via caregiver's report using the Child Behavior Checklist (CBCL; Achenbach, 1991). The CBCL contains 112 items concerning a child's behavior, including internalizing (77 items) and externalizing behavior (35 items), within the past 12 months. The externalizing subscale is comprised of the aggression (e.g., "Cruelty, bullying, or meanness to others"), and delinquency (e.g., "Breaks rules at home, school, or elsewhere") subscales. Items are rated on a 3-point scale ranging from 0 (not true) to 2 (very true or often true). The total externalizing score was computed as the sum of all relevant items for each participant. Internal consistency of the externalizing subscale (Cronbach's α) was 0.73 in our sample. The externalizing scores (**Figure 1A**; mean: 5.9, *SD* = 5.3) were positively skewed in our sample with a skewness of 2.39 [standard error (*SE*) = 0.43] and kurtosis of 8.39 (*SE* = 0.85).

Callous-Unemotional (CU) Traits

Both caregivers and youth participants filled out their respective versions of the Inventory of Callous Unemotional traits (ICU; Frick, 2004). The ICU is a 24-item questionnaire developed to provide a more comprehensive assessment of CU traits, composited of the callous, uncaring, and unemotional subscales. It is a 4-point rating scale ranging from 0 (not at all true) to 3 (definitely true). The total caregiver-report and self-report CU trait scores were computed separately for each participant. One participant's self-report data in the callous subscale had one missing item, which was replaced by the average score of the other items in this subscale. Internal consistency of the caregiver-report CU scores for our sample was high (α = 0.89), while the self-report was acceptable (α = 0.61). The greater score of the two reports (e.g., caregiver- vs. self-report) was used to compute the final CU trait score for each participant, as recommended by the ICU and Antisocial Process Screening Device Manual (Frick and Hare, 2001). The CU scores (**Figure 1B**; mean: 24.9, *SD* = 7.9) were positively skewed in our sample with a skewness of 0.62 (*SE* = 0.43) and kurtosis of −0.59 (*SE* = 0.85).

Pubertal Status

Adolescents filled out the Self-Rating Scale for Pubertal Development (Carskadon and Acebo, 1993). Its rating is based on a 4-point scale: 1 ("has not yet begun"), 2 ("has barely"),

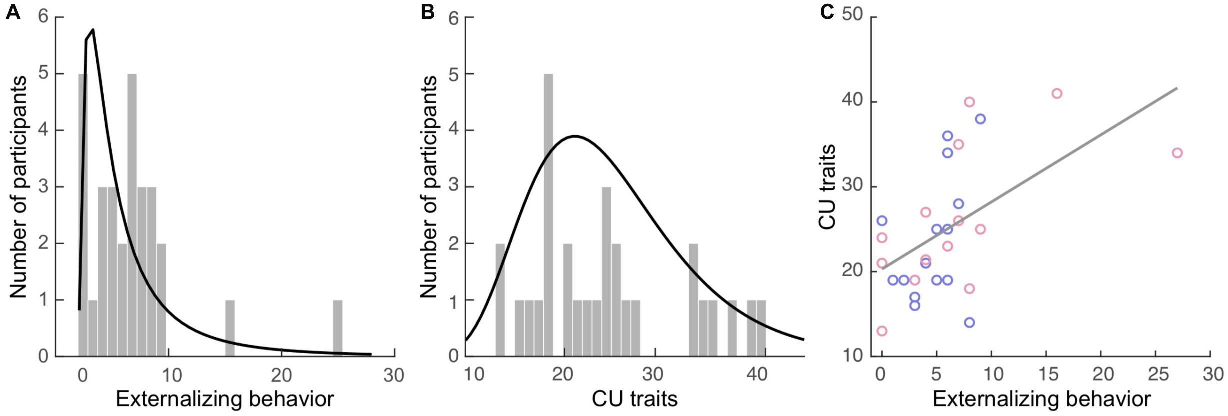

FIGURE 1 | Externalizing behavior and callous-unemotional (CU) traits in the current sample. Histograms of the **(A)** externalizing behavior and **(B)** CU traits. The curves in black represent the fitted distributions. **(C)** Positive correlation between these two measures. Blue dots: boys. Red dots: girls.

3 ("definitely underway"), 4 ("seem complete"), or unknown (i.e., "I don't know"). It contains three questions for both boys and girls regarding growth in height, body hair growth, and skin changes. Girls answer two additional questions about breast growth and menstruation (and a third question about the age of menstruation, if applicable), while boys answer two additional questions regarding deepening of the voice and facial hair growth. A pubertal status score (prepubertal, early pubertal, mid pubertal, late pubertal, or postpubertal) was computed for each participant based on guidelines from (Crockett, unpublished).

In addition, participants' IQ scores and social adversity levels were acquired when they were initially recruited. Full-scale IQ was estimated using four subtests of the Wechsler Intelligence Scale for Children-Fourth Edition (WISC-IV; Wechsler, 2003): Verbal Comprehension Index (VCI), Perceptual Reasoning Index (PRI), Working Memory Index (WMI), and Processing Speed Index (PSI). The four-factor indices of the WISC-IV have high reliabilities, ranging from Cronbach's α of 0.88 to 0.94 (Kaufman et al., 2006). For this study, we assessed VCI using the Vocabulary task, WMI using the Digit Span task, PRI using the Matrix Reasoning task, and PSI using the Coding task. The total scaled score across the three subtests was then converted to the estimated FS-IQ following the Tellegen and Briggs procedure (Tellegen and Briggs, 1967).

A social adversity index was computed from the caregiver's responses to ten questions based on previous literature (Raine, 2002; Gao et al., 2010a; Zhang and Gao, 2015). A total adversity score was created by adding 1 point for each of the following variables: Divorced Parents (single-parent family, remarriage, or living with guardians other than parents), Foster Home, Public Housing, Welfare Food Stamps, Parent Ever Arrested (either parent has been arrested at least once), Parents Physically Ill, Parents Mentally Ill, Crowded Home (five or more family members per room within the home), Teenage Mother (aged 19 years or younger when the child was born), and Large Family (having five or more siblings by 3 years of age). Items were scored dichotomously with a 0 (no) or 1 (yes). Higher total scores reflect higher social adversity.

Monetary Incentive Delay (MID) Task

We employed a modified version of the Monetary Incentive Delay Task (**Figure 2**), adapted from Knutson et al. (2001a) and Samanez-Larkin et al. (2007), to examine the reward and punishment related brain responses. In this task, a Pavlovian conditioning procedure was used with each trial including two phases of interest: anticipation and outcome. The anticipation phase begins with a geometric visual cue displayed for 2000 milliseconds (ms) followed by a 2000–2500 ms central fixation crosshair, with an average total length of 4.26 (*SD* = 0.01, range = 4.0 - 4.5) seconds (s). Each geometric cue was associated with a particular outcome: the circle (reward cue) was associated with potential reward (monetary gain), the square (punishment cue) was associated with potential punishment (monetary loss), and the triangle (neutral cue) was associated with no gain or loss. Participants were explicitly told the meaning of each geometric cue when the task was being explained prior to the practice session. Immediately after the anticipation phase, a pentacle appears on the center of the screen for a short period as a target and participants were required to hit the response button as soon as they detected the target. Only responses

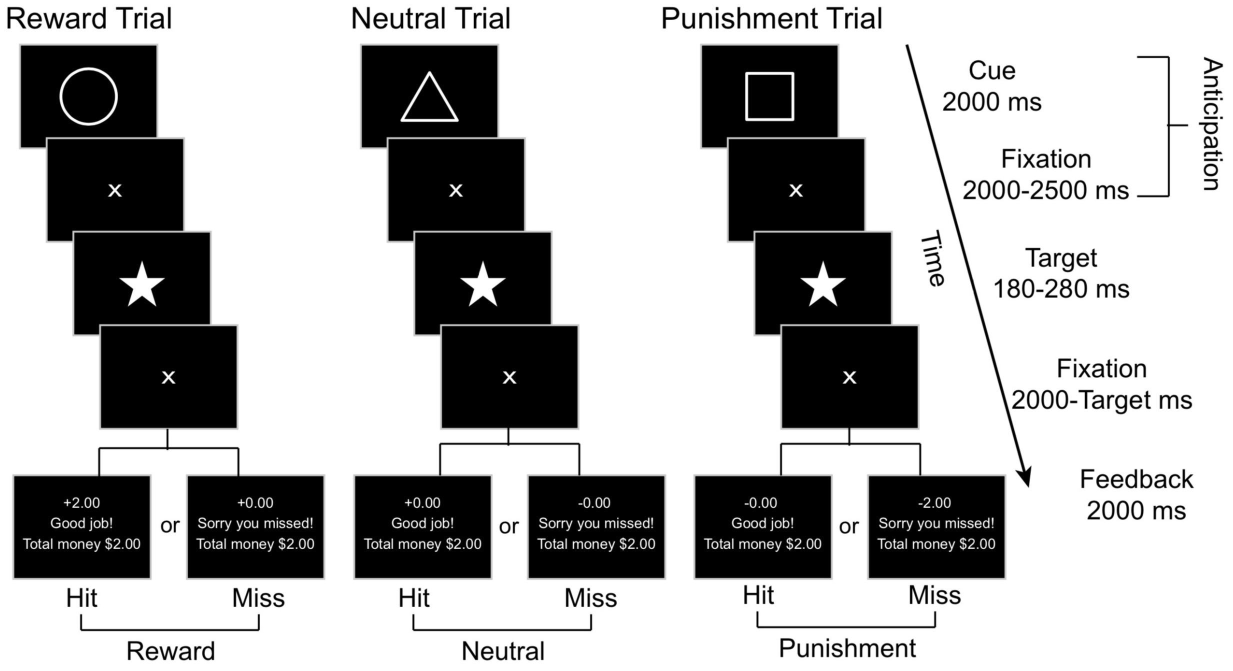

FIGURE 2 | A schematic representation of the MID task, where affectively neutral geometric cues signify the trial type (e.g., reward, neutral, or punishment). Subjects are instructed to press a button as soon as they observe the star target and are given feedback based on their performance toward the end of each trial.

made within the window of target duration were considered as correct responses.

For each participant, the initial target duration was set as the mean response time from the 18 practice trials. For each of the following trials, the target duration was adaptively altered based on performance on prior trials to limit the current total hit rates as 66%. A fixation cross was displayed after the target for 2000 ms minus the target duration. Then, in the outcome phase, the feedback was provided for 2000 ms, including response accuracy ("Good job!" for target hit within the time window and "Sorry you missed!" for missed target), together with trial-specific and cumulative rewards earned. If the target was hit within the time window after a reward cue (circle), participants would win \$2.00; otherwise, they would gain \$0.00. Hit after a punishment cue resulted in losing \$0.00, whereas a miss would result in losing \$2.00. Hit or miss after a neutral cue resulted in neither gain nor loss (±\$0.00). The inter-trial interval was 2000–3000 ms. There were 45 trials in each run, including 15 reward, punishment, and neutral trials each, presented in random order. Each run began with a 15 s fixation period and ended with another 15 s fixation period followed by a feedback of the total rewards earned from the current run. Each run lasted about 9.5 min. There were two runs for each participant, resulting in a total of 90 trials lasting about 19 min.

fMRI Data Acquisition

MRI acquisitions were obtained on a 3T Siemens Magnetom Skyra scanner with a 32-channel phase-array coil at the ISMMS. Each scan session lasted about 50 min. Foam padding was used to minimize participants' head movement. All images were acquired along axial planes parallel to the anterior commissure-posterior commissure (AC–PC) line. Two runs of T2*-weighted images for fMRI were acquired during the task with a Multi-band accelerated EPI pulse sequence[1] with the following parameters: 60 axial slices of 2.4 mm thick, interleaved, skip = 0 mm, TR = 1000 ms, TE = 35 ms, multi-band accel. factor = 6, echo spacing = 0.72 ms, flip angle = 77°, FOV = 228 mm, matrix size = 96 × 96, voxel size = 2.4 mm × 2.4 mm × 2.4 mm. Each run began with a single-band reference image that matched real brain-volumes and acquired without acceleration, followed by 540 volumes covering the task period. A pair of spin-echo echo-planar imaging (SE-EPI) reverse-phase encode field maps were acquired prior to these two runs, with TR = 8600 ms and TE = 65 ms. A high-resolution T1-weighted anatomical volume of the whole brain was acquired after the task with a magnetization-prepared rapid gradient-echo (MPRAGE) sequence with the following parameters: 176 axial slices of 1.0 mm thick, skip = 0 mm, TR = 2400 ms, TE = 1.94 ms, flip angle = 8°, FOV = 256 mm, matrix size = 256 × 256, voxel size = 1.0 mm × 1.0 mm × 1.0 mm.

Procedure

The task was compiled and executed via E-prime 2.0 software (Psychology Software Tools, Pittsburgh, PA, United States). Stimuli were projected onto a screen placed at the back of the magnet bore and viewed with mirrors mounted on the head coil. Prior to scanning, the task was explained to the adolescents via written and verbal instructions, and then they performed an 18-trial practice session on a PC. A mock scanner with an identical stimulus presentation and response system was shown to each participant to help them acclimate to the MRI environment. MRI-compatible lenses were provided to adolescents who required vision correction. Their responses were collected using a fiber-optic button system with a five-button response glove (BrainLogic, Psychology Software Tools) placed on their dominant hand. Participants were required to make responses by pressing the button under their index finger. At the end of the experiment, participants were debriefed.

Imaging Preprocessing

Image preprocessing was performed for each participant using the statistical parametric mapping package (SPM 12; Wellcome Trust Center for Neuroimaging, London, United Kingdom; RRID:SCR_007037) and FMRIB Software Library (FSL v6.0[2]; RRID:SCR_002823). The T1 image and all EPI images were manually adjusted to align the AC-PC plane. Bias correction was performed for both T1 and EPI images. Each EPI image volume was then realigned to the first volume and six motion parameters were estimated. Fieldmap in Hz and magnitude images were generated based on the field map images to calculate the voxel displacement map (VDM). The VDM was applied to all EPI images to correct distortions. Head motion and signal drifting were further corrected using the ArtRepair software version 5b (RRID:SCR_005990)[3]. A mean EPI image was calculated across all EPI images after these steps of processing. The brain was extracted from the bias-corrected T1 image and coregistered to the brain extracted from the mean EPI image using normalized mutual information. The coregistered T1 brain was normalized to a bias-corrected 12-years adolescent T1 template (Richards et al., 2016), with affine regularization as ICBM space template – European brains, and resampled to a voxel size of 2 × 2 × 2 mm. Normalized EPI images were then spatially smoothed with a Gaussian kernel of 6 mm full-width half-maximum, as recommended by Sacchet and Knutson (2013) to accurately locate the VST.

General Linear Modeling (GLM)

The GLM was performed using SPM 12. First-level (single-subject level) statistical analyses of event-related blood oxygenation level-dependent (BOLD) signals were conducted using GLM for each participant. For each run, three regressors were constructed based on the onset vectors of the anticipation phase in three conditions (i.e., Reward, Neutral, and Punishment), with the duration of each event modeled as the total duration of the anticipation phase in the corresponding trial. Six regressors were constructed based on the onset vectors of the outcome phase in six feedback conditions (i.e., Reward-Hit, Reward-Miss, Neutral-Hit, Neutral-Miss, Punishment-Hit, and Punishment-Miss), with the event duration modeled as

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[1] https://www.cmrr.umn.edu/multiband/

[2] https://fsl.fmrib.ox.ac.uk/fsl/fslwiki/

[3] https://cibsr.stanford.edu/tools/human-brain-project/artrepair-software.html

0 s. For each of these six regressors, a parametric modulator of the trial-by-trial cumulative rewards earned (demeaned) was constructed to model the influence of this information on brain responses under each feedback condition. Two additional regressors were constructed based on the onset of the targets with hit and missed responses respectively, with the event duration modeled as 0 s. All of these 11 regressors were convolved with a standard hemodynamic response function (HRF). Head motion was modeled as nuisance regressors according to Friston 24-parameter model (Friston et al., 1996), including 6 head motion parameters estimated during realignment, 6 parameters as one time-point before, and 12 corresponding squared items. Low-frequency drifts in signal were removed using a high-pass filter with a 128 s cutoff. Across two runs, one nuisance regressor to indicate runs was entered into the model. The serial correlation was estimated using an autoregressive AR(1) model. This model was estimated for each participant and the images of parameter estimates (β) values were obtained for each regressor. The β images of the three anticipation-associated and six outcome-associated regressors were used in the following analyses.

For the anticipation phase, two contrasts were defined: (1) Reward cue vs. Neutral cue, to examine the involvement in gain-related anticipation, and (2) Punishment cue vs. Neutral cue, to examine the involvement in loss-related anticipation. For the outcome phase, three contrasts were defined: (1) Reward (Hit *minus* Miss) vs. Neutral (Hit *minus* Miss), to examine the involvement in reward receipt (monetary gain), and (2) Punishment (Miss *minus* Hit) vs. Neutral (Miss *minus* Hit), to examine the involvement in punishment receipt (monetary loss). For each of these four effects, a contrast image was generated for each participant.

Examining the Neural Responses Across the Entire Sample: Whole-Brain Analyses

A second-level group GLM was conducted to examine the neural responses associated with each of these four effects across the entire sample, regardless of the individual differences in externalizing behavior and CU traits. Both positive (increase) and negative (decrease) activation associated with each effect were examined. Age, sex, IQ, social adversity, and pubertal status were entered as covariates in the group-level GLM. In the group-level analysis, we used a cluster-extent thresholding approach to correct for multiple voxel comparisons. Specifically, a threshold consisted of a significance level of $p < 0.001$ (uncorrected) for the height of each voxel (as recommended by Woo et al., 2014), together with a contiguous-voxel extent threshold (k; estimated based on the random field theory; Worsley et al., 1992) was adopted, which resulted in a cluster-level $p < 0.05$ threshold.

Extracting Neural Responses From Regions of Interest (ROI)

We selected two prior defined ROI based on previous meta-analyses for fMRI studies using the MID: ventral striatum (VST), which is associated with reward processing, and amygdala, which is associated with the processing of negative emotion (Knutson and Greer, 2008; Liu et al., 2011; Richards et al., 2013; Silverman et al., 2015; Oldham et al., 2018). These two were defined anatomically. Specifically, the VST was defined according to the Oxford-GSK-Imanova structural striatal atlases (Tziortzi et al., 2011), and the amygdala was defined according to the Harvard-Oxford subcortical structural atlases. We manually traced these two ROIs on the age-specific (12-years-old) anatomical template. Signals in each ROI were defined as the first eigenvariate of the β value from all voxels within the combined cluster of that region in the left and right hemispheres. The ROI signals were extracted from each participant's first-level contrast map for each of the five effects. The statistical analyses for neural responses in ROIs (see below) are independent of the above group-level GLM analyses across the entire sample. The whole-brain exploratory regression analysis was not conducted because our sample was highly skewed on both externalizing and CU measures and the assumption of normality of variable distribution was not met.

Modeling the Influence of Externalizing and CU Traits on Neural Responses: Statistical Analyses

Primary Measures

The gender difference in both primary measures (externalizing behavior and CU traits) and measures of no interest (age, pubertal status, IQ, and social adversity) were examined using an independent sample t-test. Bootstrapped correlations between all measures were also examined. Due to the high skewness of both primary measures, the significance level of each test were estimated using bootstrapping, a non-parametric approach to estimate the population distribution of a statistical value based on the sample distribution. Specifically, a large amount of bootstrapping samples were randomly drawn from the current sample with replacement. The distribution of a statistical value computed based on each bootstrapping sample reflect the population distribution of this value (Wright et al., 2011). The bootstrapping procedure makes fewer assumptions compared to the traditional parametric approaches, and is therefore appropriate for studies with small sample size or with non-normally distributed variables. Here, for each test, 1000 bootstrapping samples were drawn from our sample, and the bias corrected and accelerated 95% confidence intervals (BCa 95% CI) of the statistical values were estimated, which adjusted for bias and skewness in the bootstrapped distribution.

Neural Responses

Due to the high skewness of both externalizing and CU scores in our sample, bootstrapping regression (Paparoditis and Politis, 2005) was conducted for the subsequent analyses (number of bootstrapping samples = 1,000, BCa 95% CI was estimated). We examined the direct effect of externalizing behavior and CU traits on ROI activation using a regression model with ROI activation associated with each of the contrast effects defined above as the dependent variable. Age, child sex, IQ, social adversity, and pubertal status were entered as covariates in Step 1, and the primary variable (i.e., externalizing behavior or CU traits) was entered in Step 2 (Model 1). The amount of variance explained by the regressor of interest was estimated as the difference of R^2 between the model and the comparable model in which only all regressors of no interest were included.

If both externalizing and CU scores were significantly associated with ROI activation, we then examined the effect of each primary variable of interest and brain activation when controlling for the non-focal variable by entering it as a regressor of no interest (Model 2). We also compared the R^2 of this model to Model 1 ($\Delta R^2 = R^2_{\text{model 2}} - R^2_{\text{model 1}}$). A reduction of R^2 (negative ΔR^2) indicates a joint contribution of these two variables, while an augment of R^2 (positive ΔR^2) reflects an antagonistic effect.

The joint contribution of externalizing behavior and CU traits on the regional activation was examined using a bootstrapping regression model (Model 3) with covariates of no interest (Step 1), both externalizing behavior and CU traits (Step 2) and their interaction as the predictor of interest (Step 3). The interaction term was computed as the product of these two variables (demeaned). A significant positive coefficient of the interaction term would indicate a superadditive effect of the two (i.e., individuals with higher levels in both CU traits and externalizing behavior are hyper-responsive). A significant negative coefficient of the interaction term would indicate a subadditive effect (i.e., individuals with lower levels of CU traits but higher levels of externalizing behavior are hyper-responsive). Compared to the regression model with only externalizing behavior and CU traits as regressors, an augment of R^2 (positive ΔR^2) of the model with an additional interaction term reflects an incremental contribution of this interaction term on predicting brain activation.

RESULTS

Descriptive Statistics of the Measures

The group-mean externalizing and CU scores together with other measures and sex differences are reported in **Table 1**. Boys and girls did not significantly differ on either externalizing ($p = 0.430$) or CU ($p = 0.559$) scores. Therefore, sex difference was not examined in the subsequent analyses. Boys and girls were also not significantly different on any of the measures of no interest except for pubertal status ($p = 0.009$, with girls showing a higher level of pubertal status than boys).

Externalizing and CU scores were significantly correlated ($r = 0.54$, BCa 95% CI: 0.264 to 0.778; $p = 0.039$), see **Figure 1C**, but this correlation became non-significant when controlling all covariates ($r = 0.58$, BCa 95% CI: 0.154 to 0.826; $p = 0.055$). None of the covariates were significantly correlated with externalizing or CU measures except puberty, which was positively correlated with the CU score ($r = 0.40$, BCa 95% CI: 0.086 to 0.694; $p = 0.031$).

Results of GLM Analysis Regardless of Individual Difference

A significant Reward cue > Neutral cue effect was shown in the VST bilaterally, while no region showed a significant Reward cue < Neutral cue effect (**Figure 3**). No significant difference between Punishment cue and Neutral cue was found in any brain region. In addition, a significant Reward (Miss *minus* Hit) < Neutral (Miss *minus* Hit) effect was shown in left inferior frontal gyrus, while no region showed a significant Reward (Miss *minus* Hit) > Neutral (Miss *minus* Hit) effect. A significant Punishment (Miss *minus* Hit) < Neutral (Miss *minus* Hit) effect was shown in hippocampus/parahippocampal gyrus bilaterally, while no region showed a significant Punishment (Miss *minus* Hit) > Neutral (Miss *minus* Hit) effect. Coordinates of the peak of each cluster showing significant activation are listed in **Table 2**.

Results of ROI Analysis

Reward-Related Anticipation

Associations between each primary variable of interest (i.e., externalizing behavior and CU traits) and activation in each ROI during reward anticipation are illustrated in **Figure 4A**. Activation in the VST was significantly positively associated with CU traits ($\beta = 0.053$, BCa 95% CI: 0.008 to 0.095; $p = 0.046$), but no significant association was found for externalizing behavior ($\beta = 0.065$, BCa 95% CI: −0.023 to 0.159; $p = 0.071$). When controlling for externalizing score, the CU-VST activation relationship became non-significant ($\beta = 0.042$, BCa 95% CI: −0.018 to 0.111; $p = 0.166$, $\Delta R^2 = -0.17$). Similarly, when controlling for CU, the externalizing–VST relationship was non-significant ($\beta = 0.033$, BCa 95% CI: −0.005 to 0.074; $p = 0.188$,

TABLE 1 | Group means, standard deviations (SD), ranges, and group-comparisons (by sex) of each measure.

	All			Boys			Girls			Sex difference
	n = 29			*n* = 14			*n* = 15			
	Mean	*SD*	Range	Mean	*SD*	Range	Mean	*SD*	Range	*p*
Age	12.3	0.8	11∼14	12.6	0.6	11∼13	12.0	0.9	11∼14	0.078
IQ	100.7	22.0	59∼154	104.1	24.5	59∼154	97.6	19.7	65∼131	0.431
Social adversity	3.2	2.2	0∼8	2.8	2.2	0∼7	3.7	2.3	0∼8	0.300
Puberty	3.6	0.9	2∼5	3.1	0.6	2∼4	4.0	1.0	3∼5	0.009
Externalizing	5.9	5.3	0∼27	5.0	2.4	0∼9	6.7	7.1	0∼27	0.430
CU	24.9	7.9	13∼40	24.1	7.6	14∼38	25.8	8.3	13∼40	0.556

CU; callous-unemotional traits.

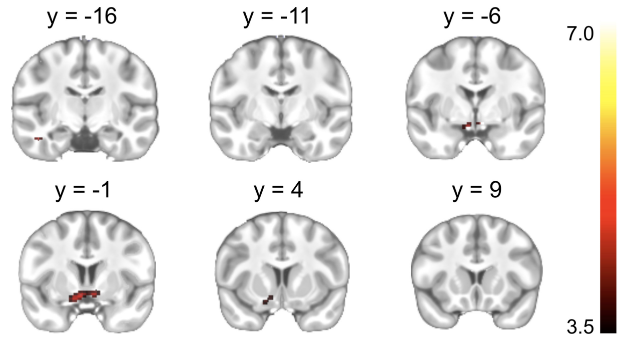

FIGURE 3 | Brain regions showing significant activation changes during the reward anticipation (Reward cue *minus* Neutral cue contrast). Color map indicates the T values.

$\Delta R^2 = -0.17$). These findings suggest that there was a substantial overlap between the contributions of CU and externalizing to VST activation. Externalizing behavior and CU traits explained 23.3 and 22.8% of the variance of the activation in the VST, respectively. The externalizing by CU interaction term in the moderation model was not significant (β = 0.08, BCa 95% CI: −0.008 to 0.020; *p* = 0.186).

Activation in the amygdala was not significantly associated with either externalizing behavior (β = −0.007, BCa 95% CI: −0.041 to 0.068; *p* = 0.822) or CU traits (β = 0.014, BCa 95% CI: −0.017 to 0.045; *p* = 0.366). The externalizing behavior by CU interaction term in the moderation model was not significant (β = 0.004, BCa 95% CI: −0.006 to 0.020; *p* = 0.358).

Punishment-Related Anticipation

Associations between externalizing behavior/CU traits and activation in each ROI during punishment anticipation are illustrated in **Figure 4B**. Activation in the VST was not associated with either externalizing behavior (β = −0.036, BCa 95% CI: −0.103 to 0.076; *p* = 0.118) or CU traits (β = 0.018, BCa 95% CI: −0.035 to 0.084; *p* = 0.523). Externalizing behavior and CU traits explained 4.6 and 1.7% of the variance of the activation in the VST, respectively. The externalizing behavior by CU interaction effect in the moderation model was not significant (β = −0.001, BCa 95% CI: −0.016 to 0.022; *p* = 0.858).

Activation in the amygdala was not significantly associated with either externalizing behavior (β = −0.045, BCa 95% CI: −0.090 to 0.060; *p* = 0.262) or CU traits (β = 0.015, BCa 95% CI: −0.045 to 0.074; *p* = 0.616). Externalizing behavior and CU traits explained 6.9 and 1.1% of the variance of the activation in the amygdala, respectively. The externalizing behavior by CU interaction effect in the moderation model was not significant (β = −0.003, BCa 95% CI: −0.017 to 0.033; *p* = 0.677).

Reward Receipt (Monetary Gain) Related Responses

Associations between externalizing behavior/CU and activation in each ROI during the receipt of reward (monetary gain) are illustrated in **Figure 4C**. Activation in the VST was not significantly associated with either externalizing behavior (β = 0.266, BCa 95% CI: −0.173 to 0.502; *p* = 0.058) or CU traits (β = 0.202, BCa 95% CI: −0.066 to 0.507; *p* = 0.119). Externalizing behavior and CU traits explained 17.0 and 14.4% of the variance of the activation in the VST, respectively. The externalizing behavior by CU interaction effect in the moderation model was not significant (β = −0.006, BCa 95% CI: −0.053 to 0.030; *p* = 0.785).

Activation in the amygdala was not significantly associated with either externalizing behavior (β = 0.142, BCa 95% CI: −0.143 to 0.241; *p* = 0.137) or CU traits (β = −0.019, BCa 95% CI: −0.183 to 0.144; *p* = 0.808). Externalizing behavior and CU traits explained 8.6 and 0.2% of the variance of the activation in the amygdala, respectively. The externalizing behavior by CU interaction effect in the moderation model was not significant (β = 0.004, BCa 95% CI: −0.046 to 0.033; *p* = 0.820).

Punishment Receipt (Monetary Loss) Related Responses

Associations between externalizing behavior/CU and activation in each ROI during the receipt of punishment (monetary loss) are illustrated in **Figure 4D**. Activation in the VST was not significantly associated with either externalizing behavior (β = −0.101, BCa 95% CI: −0.289 to 0.086; *p* = 0.275) or CU traits (β = −0.011, BCa 95% CI: −0.170 to 0.147; *p* = 0.883). Externalizing behavior and CU traits explained 4.9 and 0.1% of the variance of the activation in the VST, respectively. The externalizing behavior by CU interaction effect in the moderation model was not significant (β = 0.025, BCa 95% CI: −0.030 to 0.089; *p* = 0.095).

Activation in the amygdala was significantly associated with externalizing behavior (β = −0.155, BCa 95% CI: −0.305 to −0.006; *p* = 0.042), and remained significant after controlling for CU (β = −0.226, BCa 95% CI: −0.375 to −0.091; *p* = 0.004, $\Delta R^2 = 0.06$). CU traits were not significantly associated with activation in the amygdala (β = −0.008, BCa 95% CI: −0.167 to 184; *p* = 0.903). Externalizing behavior and CU traits explained 14.6 and 0.1% of the variance of the activation in the amygdala, respectively. The externalizing behavior by CU interaction effect in the moderation model was not significant (β = 0.007, BCa 95% CI: −0.021 to 0.044; *p* = 0.583).

DISCUSSION

The present study examined the neural mechanisms of reward and punishment processing in relation to externalizing behavior and CU traits (individually and jointly) in a community sample of adolescents. Findings provide partial support for the theories of hyper-responsivity to reward and hypo-responsivity to punishment in CU and externalizing youths.

Partially consistent with our hypothesis of hyper-responsivity to reward in youths with high externalizing behavior and/or CU traits, CU traits were positively correlated with VST activation during reward anticipation. Similar positive relationship with VST activation was also found for externalizing behavior, although it was non-significant (*p* = 0.071), likely due to the small sample size. We also demonstrated that externalizing behavior and CU traits share substantial overlap in predicting

TABLE 2 | Brain regions showing significant activation changes in the GLM analysis.

Regions	L/R	BA	*x*	*y*	*z*	*T*	*Z*	*K*
Reward cue > Neutral cue								
Ventral striatum	L		−8	−4	−10	4.74	3.92	135
Ventral striatum	R		6	−2	−6	4.46	3.75	
Feedback: Reward (Hit - Miss) < Neutral (Hit - Miss)								
Inferior frontal gyrus	L	47	−22	26	−6	5.19	4.18	90
Feedback: Punishment (Miss - Hit) < Neutral (Miss - Hit)								
Hippocampus/Parahippocampal gyrus	R	27/35	22	−28	−6	5.66	4.44	226
Hippocampus/Parahippocampal gyrus	L	27/35	−20	−34	−4	5.03	4.09	106

Regions are listed in a descending order based on their peak Z value. For a cluster with multiple local peaks, the number of voxels in the whole cluster (K) was only listed under the first local peak (also for other activation tables). The threshold was $p < 0.001$ *for the height and cluster level* $p < 0.05$*. L, left; R, right. BA, Brodmann area.*

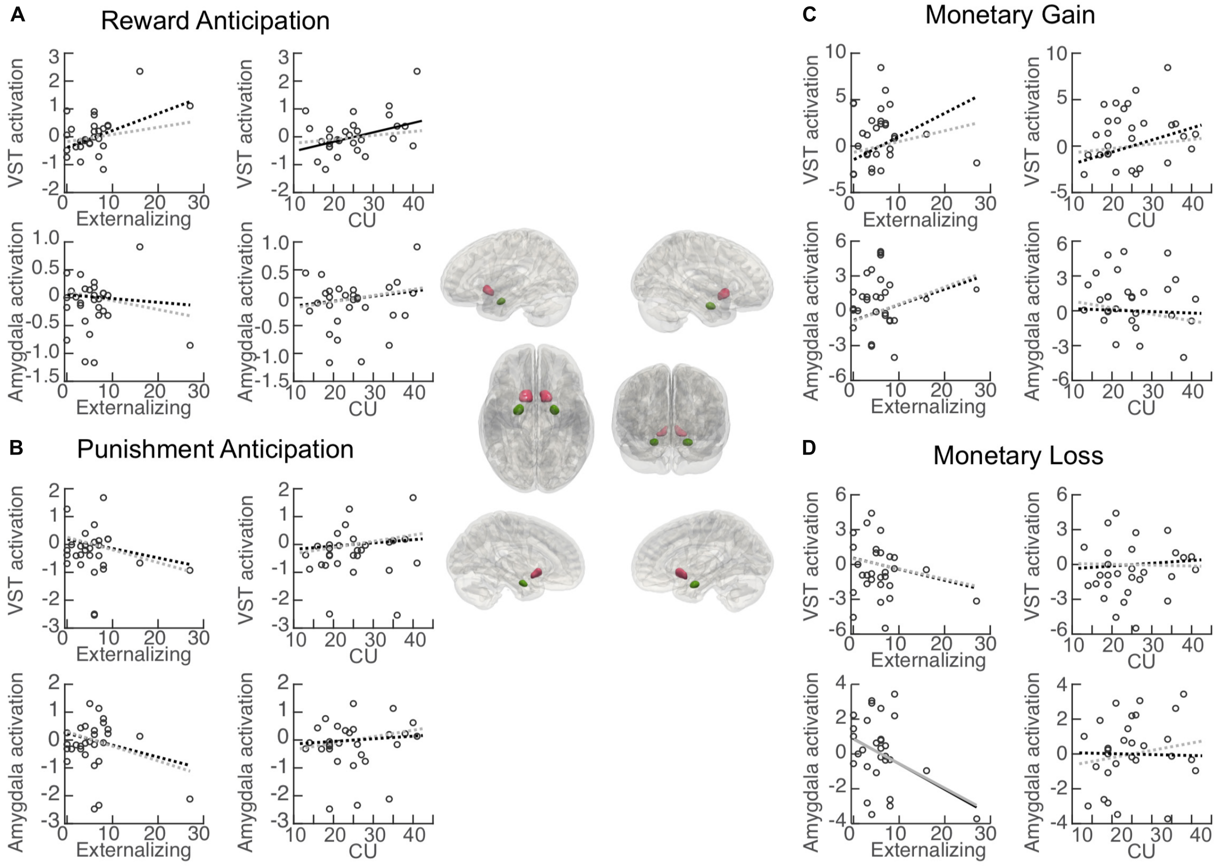

FIGURE 4 | Association between primary measures and activation in regions of interest (ROI). Central panel: Illustration of the anatomically defined ROI of the ventral striatum (VST) and amygdala. Correlation (black lines) and partial correlation (gray lines) between externalizing behavior/CU traits and ROI activation during **(A)** reward anticipation (Reward cue minus Neutral cue); **(B)** punishment anticipation (Punishment cue minus Neutral cue); **(C)** reward (monetary gain) [Reward (Hit *minus* Miss) minus Neutral (Hit *minus* Miss)], and **(D)** punishment (monetary loss) [Punishment (Miss *minus* Hit) minus Neutral (Miss *minus* Hit)]. Solid lines: significant association. Dashed lines: non-significant association.

activation of the VST during reward anticipation, given that once the effect of the non-focal variable was taken into account, the associations became non-significant. Abnormal anticipatory responses in the VST have been suggested as a biomarker for various high-risk (e.g., impulsive, addicted) populations (see Balodis and Potenza, 2015 for a review), particularly in the context of reward anticipation. In contrast, some psychiatric (e.g., schizophrenia, depression) conditions have been associated with blunted activation in the VST (Knutson and Heinz, 2015). Taken together, hyperactivity in the VST may be potentially used to predict future problematic and risky behaviors that are reward dominant, including externalizing behavior, CU traits, substance abuse, and gambling (Blaszczynski et al., 1997; King et al., 2004).

Partly in line with our hypothesis of hypo-responsivity to punishment, we found that externalizing scores were negatively associated with the amygdala responses to monetary loss during punishment receipt (with or without controlling CU traits). Specifically, adolescents with fewer externalizing behaviors showed stronger amygdala activation when the outcome of missing the target was accompanied by a punishment as monetary loss (Miss *minus* Hit after the punishment cue), compared to the same outcome but with no punishment (Miss *minus* Hit after the neutral cue). However, for individuals with higher externalizing scores, they showed weaker amygdala activation when missing the target was accompanied by a punishment (see **Figure 4B**), suggesting that the neural processing of punishment may be suppressed in adolescents with more externalizing behaviors. These results are similar to previous research study on DBD youth (e.g., Finger et al., 2011) that found amygdala deactivation in response to punishment receipt.

In addition, no significant interaction effect between CU and externalizing was found for any of the ROIs when anticipating or receiving rewards or punishment, failing to support our hypothesis that individuals with higher levels of both externalizing behavior and CU traits would show the most salient abnormalities in brain activation. It is worth noting that our study is the first to examine the interaction effects of CU and externalizing behavior on reward/punishment anticipation and processing. Prior functional brain imaging studies that examined additive effects of CU and externalizing measures (e.g., Herpertz et al., 2008; Passamonti et al., 2010) had focused on neural processing of emotional stimuli. In addition, interactive effects of CU and externalizing measures seem to be more prominent in the amygdala activation during fear-related processing in particular (Viding et al., 2012; Cardinale et al., 2018). Finally, our null findings may also be due to low statistical power, and future studies with larger sample size should be conducted to detect if any interaction effects may exist using reward and punishment-related paradigms.

Alternatively, the lack of effect may be partly due to the nature of the task (e.g., more anticipation events relative to feedback), which ultimately makes it less powerful for detecting effects for reward receipt. Relatedly, the MID task has been extensively used to assess reward processing, but less for punishment processing (Oldham et al., 2018). Potentially, this task may be less sensitive to punishment anticipation than to reward anticipation. In fact, studies utilizing the MID have more often linked personality traits to VST activation to reward than to punishment (e.g., Buckholtz et al., 2010; Bjork et al., 2012).

The current research also has caveats to consider. First, the sample size is small, limiting statistical power. Moreover, the externalizing and CU scores were highly skewed in our sample. Two participants had very high scores on these measures, with one having an externalizing score (27) greater than 2 SD (but less than 3 SD) of the group mean, and the other having a CU score (41) greater than 2 SD (but less than 3 SD) of the group mean. Normative samples of adolescents aged 12–14 years have reported CBCL externalizing behavior means of 7.01 and 5.38 for boys and girls, respectively (Bongers et al., 2003). Means for CU traits (via the ICU) range from 23.45 to 31.05 in community adolescent samples (Roose et al., 2010; Feilhauer et al., 2012). Still, we caution that our results may be less generalizable to individuals with clinical diagnosis of DBD because our range of externalizing scores (expect the one with very high score) is rather limited (e.g., 0–16), whereas prior reports of externalizing behavior for adolescent in clinical samples range from 18.92 to 27.2 (Bögels et al., 2008; Bjork et al., 2010; Schaeffer et al., 2014). Similarly, ranges for CU traits in our sample (after excluding the outliers) were diverse (13–38, mean = 23.8), while detainee and offender samples report total score means ranging from 23 to 41 (Kimonis et al., 2008, 2013; White et al., 2013). Next, although we did incorporate both sexes in our study, boys and girls did not significantly differ on externalizing behavior or CU traits in our sample. This may be due to low statistical power resulted from a small sample size. Sex differences have been found in the gray matter volumes of the OFC (Raine et al., 2011) and volumetric brain asymmetries of the OFC and ACC (Visser et al., 2013) in antisocial populations. Future work with larger sex-mixed samples is needed to determine the effects of sex, especially since there are large gender gaps for prevalence rates of externalizing disorders (Newman et al., 1996; Hicks et al., 2007). Finally, we only focused on the VST and amygdala as our ROIs because of their well-documented involvement in the reward and punishment processing (Bjork et al., 2012; Cohn et al., 2015; Oldham et al., 2018). Although the involvement of other regions including the vmPFC and insula has been reported (Knutson et al., 2001b; Balodis et al., 2012; Silverman et al., 2015; Oldham et al., 2018), our exploratory whole-brain regression analysis did not reveal any significant effects for these areas in our sample.

One strength of our work is that we recruited from an ethnically diverse and mixed-sex healthy community sample. Previous studies have primarily been on male and clinical populations (e.g., Finger et al., 2011; Bjork et al., 2012; Pujara et al., 2013; Cohn et al., 2015; Byrd et al., 2018). Only recently has the focus shifted to the inclusion of community samples with both sexes and younger age groups, which is what we were able to accomplish in this study. Taken together, our results suggest that both externalizing behavior and CU traits are associated with hyper-responsivity to reward, and that externalizing behavior in particular is associated with hypo-responsivity to punishment. As both externalizing behavior and CU traits in youth are known risk factors for criminal offending in adulthood (Hinshaw and Lee, 2003; Frick and White, 2008), it may be beneficial for future work to evaluate the degree to which externalizing problems and CU traits are independently and jointly associated with neural activity. This knowledge will help us better understand the etiological basis of externalizing problems and CU traits and eventually contribute to interventions for these unwanted trajectories.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Institutional Review Board of Brooklyn College (CUNY). Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

AUTHOR CONTRIBUTIONS

YH and YG conceived and planned the research study. YH, SF, and SL carried out the study. YH and TW preprocessed the data. YL, ZW, and XL contributed to the imaging preprocessing pipeline. TW performed the statistical analyses. YH, TW, and YG wrote the manuscript with input from all other authors. All authors provided critical feedback to all components of the research.

FUNDING

Research reported in this publication was supported by the National Institute of General Medical Sciences of the National Institutes of Health under Award Numbers SC3GM118233 and SC1GM127243 to YG. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

ACKNOWLEDGMENTS

The authors would like to thank the families for their participation, and the staff at Brooklyn College Psychophysiology Laboratory and the Translational and Molecular Imaging Institute at Mount Sinai Icahn School of Medicine for their assistance.

REFERENCES

Achenbach, T. M. (1991). *Manual for the Child Behavior Checklist/4-18 and 1991 Profile*. Burlington, VT: University of Vermont.

American Psychiatric Association [APA] (2013). *Diagnostic and Statistical Manual of Mental Disorders (DSM-5®)*. Maine Avenue SW: American Psychiatric Pub.

Balodis, I. M., Kober, H., Worhunsky, P. D., Stevens, M. C., Pearlson, G. D., and Potenza, M. N. (2012). Diminished frontostriatal activity during processing of monetary rewards and losses in pathological gambling. *Biol. Psychiatry* 71, 749–757. doi: 10.1016/j.biopsych.2012.01.006

Balodis, I. M., and Potenza, M. N. (2015). Anticipatory reward processing in addicted populations: a focus on the monetary incentive delay task. *Biol. Psychiatry* 77, 434–444. doi: 10.1016/j.biopsych.2014.08.020

Barry, C. T., Frick, P. J., DeShazo, T. M., McCoy, M., Ellis, M., and Loney, B. R. (2000). The importance of callous-unemotional traits for extending the concept of psychopathy to children. *J. Abnorm. Psychol.* 109, 335–340. doi: 10.1037/0021-843X.109.2.335

Bjork, J. M., Chen, G., and Hommer, D. W. (2012). Psychopathic tendencies and mesolimbic recruitment by cues for instrumental and passively obtained rewards. *Bio. Psychol.* 89, 408–415. doi: 10.1016/j.biopsycho.2011.12.003

Bjork, J. M., Chen, G., Smith, A. R., and Hommer, D. W. (2010). Incentive—elicited mesolimbic activation and externalizing symptomatology in adolescents. *J. Child Psychol. Psychiatry* 51, 827–837. doi: 10.1111/j.1469-7610.2009.02201.x

Blaszczynski, A., Steel, Z., and McConaghy, N. (1997). Impulsivity in pathological gambling: the antisocial impulsivist. *Addiction* 92, 75–87. doi: 10.1046/j.1360-0443.1997.921758.x

Bögels, S., Hoogstad, B., van Dun, L., de Schutter, S., and Restifo, K. (2008). Mindfulness training for adolescents with externalizing disorders and their parents. *Behav. Cogn. Psychothe.* 36, 193–209. doi: 10.11124/JBISRIR-2016-2314

Bongers, I. L., Koot, H. M., Van der Ende, J., and Verhulst, F. C. (2003). The normative development of child and adolescent problem behavior. *J. Abnorm. Psychol.* 112, 179–192. doi: 10.1037/0021-843x.112.2.179

Buckholtz, J. W., Treadway, M. T., Cowan, R. L., Woodward, N. D., Benning, S. D., Li, R., et al. (2010). Mesolimbic dopamine reward system hypersensitivity in individuals with psychopathic traits. *Nat. Neurosci.* 13, 419–421. doi: 10.1038/nn.2510

Byrd, A. L., Hawes, S. W., Burke, J. D., Loeber, R., and Pardini, D. A. (2018). Boys with conduct problems and callous-unemotional traits: neural response to reward and punishment and associations with treatment response. *Dev. Cogn. Neurosci.* 30, 51–59. doi: 10.1016/j.dcn.2017.12.004

Byrd, A. L., Loeber, R., and Pardini, D. A. (2014). Antisocial behavior, psychopathic features and abnormalities in reward and punishment processing in youth. *Clini. Child Fam. Psychol. Rev.* 17, 125–156. doi: 10.1007/s10567-013-0159-6

Calkins, S. D., and Keane, S. P. (2009). Developmental origins of early antisocial behavior. *Dev. Psychopathol.* 21, 1095–1109. doi: 10.1017/S095457940999006X

Cardinale, E. M., Breeden, A. L., Robertson, E. L., Lozier, L. M., Vanmeter, J. W., and Marsh, A. (2018). Externalizing behavior severity in youths with callous-unemotional traits corresponds to patterns of amygdala activity and connectivity during judgments of causing fear. *Dev. Psychopathol.* 30, 191–201. doi: 10.1017/S0954579417000566

Cardinale, E. M., O'Connell, K., Robertson, E. L., Meena, L. B., Breeden, A. L., Lozier, L. M., et al. (2019). Callous and uncaring traits are associated with reductions in amygdala volume among youths with varying levels of conduct problems. *Psychol. Med.* 49, 1449–1458. doi: 10.1017/S0033291718001927

Carskadon, M. A., and Acebo, C. (1993). A self-administered rating scale for pubertal development. *J. Adoles. Health* 14, 190–195. doi: 10.1016/1054-139x(93)90004-9

Charles, N. E., Acheson, A., Mathias, C. W., Furr, R. M., and Dougherty, D. M. (2012). Psychopathic traits and their association with adjustment problems in girls. *Behav. Sci. Law* 30, 631–642. doi: 10.1002/bsl.2029

Cho, Y. T., Fromm, S., Guyer, A. E., Detloff, A., Pine, D. S., Fudge, J. L., et al. (2013). Nucleus accumbens, thalamus and insula connectivity during incentive anticipation in typical adults and adolescents. *NeuroImage* 66, 508–521. doi: 10.1016/j.neuroimage.2012.10.013

Cohn, M. D., Veltman, D. J., Pape, L. E., van Lith, K., Vermeiren, R. R., van den Brink, W., et al. (2015). Incentive processing in persistent disruptive behavior and psychopathic traits: a functional magnetic resonance imaging study in adolescents. *Biol. Psychiatry* 78, 615–624. doi: 10.1016/j.biopsych.2014.08.017

Dadds, M. R., and Salmon, K. (2003). Punishment insensitivity and parenting: temperament and learning as interacting risks for antisocial behavior. *Clin. Child Fam. Psychol. Rev.* 6, 69–86.

Delgado, M. R., Jou, R. L., LeDoux, J., and Phelps, L. (2009). Avoiding negative outcomes: tracking the mechanisms of avoidance learning in humans during fear conditioning. *Front. Behav. Neurosci.* 3:33. doi: 10.3389/neuro.08.033.2009

Fagan, S. E., Zhang, W., and Gao, Y. (2017). Social adversity and antisocial behavior: mediating effects of autonomic nervous system activity. *J. Abnorm. Child Psychol.* 45, 1553–1564. doi: 10.1007/s10802-017-0262-0

Fairchild, G., Van Goozen, S. H., Stollery, S. J., and Goodyer, I. M. (2008). Fear conditioning and affective modulation of the startle reflex in male adolescents with early-onset or adolescence-onset conduct disorder and healthy control subjects. *Biol. Psychiatry* 63, 279–285. doi: 10.1016/j.biopsych.2007.06.019

Feilhauer, J., Cima, M., and Arntz, A. (2012). Assessing callous–unemotional traits across different groups of youths: further cross-cultural validation of the inventory of callous-unemotional traits. *Int. J. Law Psychiatry* 35, 251–262. doi: 10.1016/j.ijlp.2012.04.002

Finger, E. C., Marsh, A. A., Blair, K. S., Reid, M. E., Sims, C., Ng, P., et al. (2011). Disrupted reinforcement signaling in the orbitofrontal cortex and caudate in youths with conduct disorder or oppositional defiant disorder and a high level of psychopathic traits. *Am. J. Psychiatry* 168, 152–162. doi: 10.1176/appi.ajp.2010.10010129

Frick, P. J., and Dickens, C. (2006). Current perspectives on conduct disorder. *Curr. Psychiatry Rep.* 8, 59–72. doi: 10.1007/s11920-006-0082-3

Frick, P. J., and Hare, R. D. (2001). *Antisocial Process Screening Device: APSD*. Toronto: Multi-Health Systems.

Frick, P. J., and Marsee, M. A. (2006). "Psychopathy and developmental pathways to antisocial behavior in youth," in *The Handbook of Psychopathy*, ed. C. J. Patrick, (New York, NY: Guilford Press), 353–375.

Frick, P. J., Ray, J. V., Thornton, L. C., and Kahn, R. E. (2014). Can callous-unemotional traits enhance the understanding, diagnosis, and treatment of serious conduct problems in children and adolescents? A comprehensive review. *Psychol. Bul.* 140:1–57. doi: 10.1037/a0033076

Frick, P. J. (1995). Callous-unemotional traits and conduct problems: a two-factor model of psychopathy in children. *Issues Criminol. Legal Psychol.* 24, 47–51.

Frick, P. J. (2004). *The Inventory of Callous-Unemotional Traits*. New Orleans, LA: University of New Orleans.

Frick, P. J., and White, S. F. (2008). Research review: the importance of callous-unemotional traits for developmental models of aggressive and antisocial behavior. *J. Child Psychol. Psychiatry* 49, 359–375. doi: 10.1111/j.1469-7610.2007.01862.x

Friston, K. J., Williams, S., Howard, R., Frackowiak, R. S., and Turner, R. (1996). Movement-related effects in fMRI time−series. *Magn. Reson. Med.* 35, 346–355. doi: 10.1002/mrm.1910350312

Fung, M. T., Raine, A., Loeber, R., Lynam, D. R., Steinhauer, S. R., Venables, P. H., et al. (2005). Reduced electrodermal activity in psychopathy-prone adolescents. *J. Abnorm. Psychol.* 114, 187–169.

Gao, Y., Raine, A., Chan, F., Venables, P. H., and Mednick, S. (2010a). Early maternal and paternal bonding, childhood physical abuse and adult psychopathic personality. *Psychol. Med.* 40, 1007–1016. doi: 10.1017/S0033291709991279

Gao, Y., Raine, A., Venables, P. H., Dawson, M. E., and Mednick, S. A. (2010b). The development of skin conductance fear conditioning in children from ages 3 to 8 years. *Dev. Sci.* 13, 201–212. doi: 10.1111/j.1467-7687.2009.00874.x

Gao, Y., Raine, A., Venables, P. H., Dawson, M. E., and Mednick, S. A. (2009). Association of poor childhood fear conditioning and adult crime. *Am. J. Psychiatry* 167, 56–60. doi: 10.1176/appi.ajp.2009.09040499

Gao, Y., and Zhang, W. (2016). Confirmatory factor analyses of self-and parent-report inventory of callous-unemotional traits in 8-to 10-year-olds. *J. Psychopathol. Behav. Assess.* 38, 331–340. doi: 10.1007/s10862-015-9527-5

Hare, R. D. (2003). *The Psychopathy Checklist–Revised*. Toronto, ON: Multi-Health Systems.

Hawes, D. J., and Dadds, M. R. (2005). The treatment of conduct problems in children with callous-unemotional traits. *J. Consult. Clin. Psychol.* 73, 737. doi: 10.1037/0022-006x.73.4.737

Herpertz, S. C., Huebner, T., Marx, I., Vloet, T. D., Fink, G. R., Stoecker, T., et al. (2008). Emotional processing in male adolescents with childhood−onset conduct disorder. *J. Child Psychol. Psychiatry* 49, 781–791–741.

Herpertz, S. C., Mueller, B., Wenning, B., Qunaibi, M., Lichterfeld, C., and Herpertz-Dahlmann, B. (2003). Autonomic responses in boys with externalizing disorders. *J. Neural Transm.* 110, 1181–1195. doi: 10.1007/s00702-003-0026-6

Herting, M. M., and Sowell, E. R. (2017). Puberty and structural brain development in humans. *Front. Neuroendocrinol.* 44, 122–137. doi: 10.1016/j.yfrne.2016.12.003

Hicks, B. M., Blonigen, D. M., Kramer, M. D., Krueger, R. F., Patrick, C. J., Iacono, W. G., et al. (2007). Gender differences and developmental change in externalizing disorders from late adolescence to early adulthood: a longitudinal twin study. *J. Abnorm. Psychol.* 116, 433–447. doi: 10.1037/0021-843x.116.3.433

Hinshaw, S. P., and Lee, S. S. (2003). "Conduct and oppositional defiant disorders," in *Child Psychopathology* , 2nd. Edn. eds E. J. Mash, and R. A. Barkley, (New York, NY: Guilford Press), 144–198.

Hyde, L. W., Shaw, D. S., and Hariri, A. R. (2013). Understanding youth antisocial behavior using neuroscience through a developmental psychopathology lens: review, integration, and directions for research. *Dev. Rev.* 33, 168–223. doi: 10.1016/j.dr.2013.06.001

Jones, A. P., Laurens, K. R., Herba, C. M., Barker, G. J., and Viding, E. (2009). Amygdala hypoactivity to fearful faces in boys with conduct problems and callous-unemotional traits. *Am. J. Psychiatry* 166, 95–102. doi: 10.1176/appi.ajp.2008.07071050

Kaufman, A. S., Flanagan, D. P., Alfonso, V. C., and Mascolo, J. T. (2006). Test review: wechsler intelligence scale for children, (WISC-IV). *J. Psychoeduc. Assess.* 24, 278–295.

Kimonis, E. R., Cross, B., Howard, A., and Donoghue, K. (2013). Maternal care, maltreatment and callous-unemotional traits among urban male juvenile offenders. *J. Youth Adolesc.* 42, 165–177. doi: 10.1007/s10964-012-9820-5

Kimonis, E. R., Frick, P. J., Skeem, J. L., Marsee, M. A., Cruise, K., Munoz, L. C., et al. (2008). Assessing callous-unemotional traits in adolescent offenders: validation of the inventory of callous-unemotional traits. *Int. J. Law Psychiatry* 31, 241–252. doi: 10.1016/j.ijlp.2008.04.002

King, S. M., Iacono, W. G., and McGue, M. (2004). Childhood externalizing and internalizing psychopathology in the prediction of early substance use. *Addiction* 99, 1548–1559. doi: 10.1111/j.1360-0443.2004.00893.x

Knutson, B., Adams, C. M., Fong, G. W., and Hommer, D. (2001a). Anticipation of increasing monetary reward selectively recruits nucleus accumbens. *J. Neurosci.* 21, RC159–RC159.

Knutson, B., Fong, G. W., Adams, C. M., Varner, J. L., and Hommer, D. (2001b). Dissociation of reward anticipation and outcome with event-related fMRI. *Neuroreport* 12, 3683–3687. doi: 10.1097/00001756-200112040-00016

Knutson, B., and Greer, S. M. (2008). Anticipatory affect: neural correlates and consequences for choice. *Philos. Trans. R. Soc. Lon. Biol. Sci.* 363, 3771–3786. doi: 10.1098/rstb.2008.0155

Knutson, B., and Heinz, A. (2015). Probing psychiatric symptoms with the monetary incentive delay task. *Biol. Psychiatry* 77, 418–420. doi: 10.1016/j.biopsych.2014.12.022

Liu, J. (2004). Childhood externalizing behavior: theory and implications. *J. Child Adoles. Psychiatric Nurs.* 17, 93–103. doi: 10.1111/j.1744-6171.2004.tb00003.x

Liu, X., Hairston, J., Schrier, M., and Fan, J. (2011). Common and distinct networks underlying reward valence and processing stages: a meta-analysis of functional neuroimaging studies. *Neurosc. Biobehav. Rev.* 35, 1219–1236. doi: 10.1016/j.neubiorev.2010.12.012

Loeber, R., Burke, J. D., Lahey, B. B., Winters, A., and Zera, M. (2000). Oppositional defiant and conduct disorder: a review of the past 10 years, part I. *J. Am. Acad. Child Adolesc. Psychiatry* 39, 1468–1484.

Lozier, L. M., Cardinale, E. M., VanMeter, J. W., and Marsh, A. A. (2014). Mediation of the relationship between callous-unemotional traits and proactive aggression by amygdala response to fear among children with conduct problems. *JAMA Psychiatry* 71, 627–636. doi: 10.1001/jamapsychiatry.2013.4540

Lykken, D. T. (1995). *The Antisocial Personalities*. Mahwah, NJ: Lawrence Erlbaum Associates.

Marsh, A. A., Finger, E. C., Mitchell, D. G., Reid, M. E., Sims, C., Kosson, D. S., et al. (2008). Reduced amygdala response to fearful expressions in children and adolescents with callous-unemotional traits and disruptive behavior disorders. *Am. J. Psychiatry* 165, 712–720. doi: 10.1176/appi.ajp.2007.07071145

Matthys, W., Van Goozen, S. H., Snoek, H., and Van Engeland, H. (2004). Response perseveration and sensitivity to reward and punishment in boys with oppositional defiant disorder. *Eur. Child Adolesc. Psychiatry* 13, 362–364. doi: 10.1007/s00787-004-0395-x

Moffitt, T. E., Gabrielli, W. F., Mednick, S. A., and Schulsinger, F. (1981). Socioeconomic status, IQ, and delinquency. *J. Abnorm. Psychol.* 90, 152–156. doi: 10.1037/0021-843x.90.2.152

Newman, D. L., Moffitt, T. E., Caspi, A., Magdol, L., Silva, P. A., and Stanton, W. R. (1996). Psychiatric disorder in a birth cohort of young adults: prevalence, comorbidity, clinical significance, and new case incidence from ages 11 to 21. *J. Consult. Clin. Psychol.* 64, 552–562. doi: 10.1037/0022-006x.64.3.552

Newman, J. P., and Kosson, D. S. (1986). Passive avoidance learning in psychopathic and nonpsychopathic offenders. *J. Abnorm. Psychol.* 95, 252–256. doi: 10.1037/0021-843x.95.3.252

O'Brien, B. S., and Frick, P. J. (1996). Reward dominance: associations with anxiety, conduct problems, and psychopathy in children. *J. Abnorm. Child Psychol.* 24, 223–240. doi: 10.1007/bf01441486

Oldham, S., Murawski, C., Fornito, A., Youssef, G., Yücel, M., and Lorenzetti, V. (2018). and outcome phases of reward and loss processing: a neuroimaging meta-analysis of the monetary incentive delay task. *Hum. Brain Mapp.* 39, 3398–3418. doi: 10.1002/hbm.24184

Paparoditis, E., and Politis, D. N. (2005). Bootstrapping unit root tests for autoregressive time series. *J. Am. Stat. Assoc.* 100, 545–553. doi: 10.1198/016214504000001998

Pardini, D. A. (2006). The callousness pathway to severe violent delinquency. *Aggress. Behav.* 32, 590–598. doi: 10.1002/ab.20158

Passamonti, L., Fairchild, G., Goodyer, I. M., Hurford, G., Hagan, C. C., Rowe, J. B., et al. (2010). Neural abnormalities in early-onset and adolescence-onset conduct disorder. *Arch. Gen. Psychiatry* 67, 729–738. doi: 10.1001/archgenpsychiatry.2010.75

Patterson, C. M., and Newman, J. P. (1993). Reflectivity and learning from aversive events: toward a psychological mechanism for the syndromes of disinhibition. *Psychol. Rev.* 100, 716–736. doi: 10.1037//0033-295x.100.4.716

Pihet, S., Etter, S., Schmid, M., and Kimonis, E. R. (2015). Assessing callous-unemotional traits in adolescents: validity of the inventory of callous-unemotional traits across gender, age, and community/institutionalized status. *J. Psychopathol. Behav. Assess.* 37, 407–421. doi: 10.1007/s10862-014-9472-8

Pujara, M., Motzkin, J. C., Newman, J. P., Kiehl, K. A., and Koenigs, M. (2013). Neural correlates of reward and loss sensitivity in psychopathy. *Soc. Cogn. Affect. Neurosci.* 9, 794–801. doi: 10.1093/scan/nst054

Quay, H. C. (1993). The psychobiology of undersocialized conduct disorder: a theoretical perspective. *Dev. Psychopathol.* 5, 165–180. doi: 10.1017/s0954579400004326

Raine, A. (2002). Biosocial studies of antisocial and violent behavior in children and adults: a review. *J. Abnorm. Child Psychol.* 30, 311–326.

Raine, A., Yang, Y., Narr, K. L., and Toga, A. W. (2011). Sex differences in orbitofrontal gray as a partial explanation for sex differences in antisocial personality. *Mol. Psychiatry* 16, 227–236. doi: 10.1038/mp.2009.136

Richards, J. E., Sanchez, C., Phillips-Meek, M., and Xie, W. (2016). A database of age-appropriate average MRI templates. *NeuroImage* 124, 1254–1259. doi: 10.1016/j.neuroimage.2015.04.055

Richards, J. M., Plate, R. C., and Ernst, M. (2013). A systematic review of fMRI reward paradigms used in studies of adolescents vs. adults: the impact of task design and implications for understanding neurodevelopment. *Neurosci. Biobehav. Rev.* 37, 976–991. doi: 10.1016/j.neubiorev.2013.03.004

Roose, A., Bijttebier, P., Decoene, S., Claes, L., and Frick, P. J. (2010). Assessing the affective features of psychopathy in adolescence: a further validation of the inventory of callous and unemotional traits. *Assessment* 17, 44–57. doi: 10.1177/1073191109344153

Rubia, K., Smith, A. B., Halari, R., Matsukura, F., Mohammad, M., Taylor, E., et al. (2009). Disorder-specific dissociation of orbitofrontal dysfunction in boys with pure conduct disorder during reward and ventrolateral prefrontal dysfunction in boys with pure ADHD during sustained attention. *Am. J. Psychiatry* 166, 83–94. doi: 10.1176/appi.ajp.2008.08020212

Sacchet, M. D., and Knutson, B. (2013). Spatial smoothing systematically biases the localization of reward-related brain activity. *NeuroImage* 66, 270–277. doi: 10.1016/j.neuroimage.2012.10.056

Samanez-Larkin, G. R., Gibbs, S. E., Khanna, K., Nielsen, L., Carstensen, L. L., and Knutson, B. (2007). Anticipation of monetary gain but not loss in healthy older adults. *Nat. Neurosci.* 10, 787–791. doi: 10.1038/nn1894

Schaeffer, C. M., Henggeler, S. W., Ford, J. D., Mann, M., Chang, R., and Chapman, J. E. (2014). RCT of a promising vocational/employment program for high-risk juvenile offenders. *J. Subst. Abuse Treat.* 46, 134–143. doi: 10.1016/j.jsat.2013.06.012

Shaw, D. S., and Winslow, E. B. (1997). "Precursors and correlates of antisocial behavior from infancy to preschool," in *Handbook of Antisocial Behavior*, eds D. M. Stoff, J. Breiling, and J. D. Maser, (New York, NY: John Wiley & Sons), 148–158.

Silverman, M. H., Jedd, K., and Luciana, M. (2015). Neural networks involved in adolescent reward processing: an activation likelihood estimation meta-analysis of functional neuroimaging studies. *NeurImage* 122, 427–439. doi: 10.1016/j.neuroimage.2015.07.083

Tellegen, A., and Briggs, P. F. (1967). Old wine in new skins: grouping Wechsler subtests into new scales. *J. Consult. Psychol.* 31, 499–506. doi: 10.1037/h0024963

Tziortzi, A. C., Searle, G. E., Tzimopoulou, S., Salinas, C., Beaver, J. D., Jenkinson, M., et al. (2011). Imaging dopamine receptors in humans with [11C]-(+)-PHNO: dissection of D3 signal and anatomy. *NeurImage* 54, 264–277. doi: 10.1016/j.neuroimage.2010.06.044

Urošević, S., Collins, P., Muetzel, R., Lim, K. O., and Luciana, M. (2014). Pubertal status associations with reward and threat sensitivities and subcortical brain volumes during adolescence. *Brain Cogn.* 89, 15–26. doi: 10.1016/j.bandc.2014.01.007

van Goozen, S. H., Snoek, H., Matthys, W., van Rossum, I., and van Engeland, H. (2004). Evidence of fearlessness in behaviourally disordered children: a study on startle reflex modulation. *J. Child Psychol. Psychiatry* 45, 884–892. doi: 10.1111/j.1469-7610.2004.00280.x

Viding, E., Sebastian, C. L., Dadds, M. R., Lockwood, P. L., Cecil, C. A., De Brito, S. A., et al. (2012). Amygdala response to preattentive masked fear in children with conduct problems: the role of callous-unemotional traits. *Am. J. Psychiatry* 169, 1109–1116. doi: 10.1176/appi.ajp.2012.12020191

Visser, T. A., Ohan, J. L., Whittle, S., Yücel, M., Simmons, J. G., and Allen, N. B. (2013). Sex differences in structural brain asymmetry predict overt aggression in early adolescents. *Soc. Cogn. Affect. Neurosci.* 9, 553–560. doi: 10.1093/scan/nst013

von Borries, A. K. L., Brazil, I. A., Bulten, B. H., Buitelaar, J. K., Verkes, R. J., and De Bruijn, E. R. A. (2010). Neural correlates of error-related learning deficits in individuals with psychopathy. *Psychol. Med.* 40, 1559–1568. doi: 10.1017/S0033291709992017

Wallace, J. F., and Newman, J. P. (2008). "RST and psychopathy: associations between psychopathy and the behavioral activation and inhibition systems," in *The Reinforcement Sensitivity Theory of Personality*, ed. P. J. Corr, (Cambridge: Cambridge University Press), 398–414. doi: 10.1017/cbo9780511819384.014

Wechsler, D. (2003). *Wechsler Intelligence Scale for Children–Fourth Edition (WISC-IV)*. San Antonio, TX: The Psychological Corporation.

White, S. F., Frick, P. J., Lawing, K., and Bauer, D. (2013). Callous-unemotional traits and response to functional family therapy in adolescent offenders. *Behav. Sci. Law* 31, 271–285. doi: 10.1002/bsl.2041

White, S. F., Marsh, A. A., Fowler, K. A., Schechter, J. C., Adalio, C., Pope, K., et al. (2012). Reduced amygdala response in youths with disruptive behavior disorders and psychopathic traits: decreased emotional response versus increased top-down attention to nonemotional features. *Am. J. Psychiatry* 169, 750–758. doi: 10.1176/appi.ajp.2012.11081270

Woo, C. W., Krishnan, A., and Wager, T. D. (2014). Cluster-extent based thresholding in fMRI analyses: pitfalls and recommendations. *NeuroImage* 91, 412–419. doi: 10.1016/j.neuroimage.2013.12.058

Worsley, K. J., Evans, A. C., Marrett, S., and Neelin, P. A. (1992). Three-dimensional statistical analysis for CBF activation studies in human brain. *J. Cereb. Blood Flow a Metabol.* 12, 900–918. doi: 10.1038/jcbfm.1992.127

Wrase, J., Kahnt, T., Schlagenhauf, F., Beck, A., Cohen, M. X., Knutson, B., et al. (2007). Different neural systems adjust motor behavior in response to reward and punishment. *NeuroImage* 36, 1253–1262. doi: 10.1016/j.neuroimage.2007.04.001

Wright, D. B., London, K., and Field, A. P. (2011). Using bootstrap estimation and the plug-in principle for clinical psychology data. *J. Exp. Psychopathol.* 2, 252–270. doi: 10.5127/jep.013611

Zhang, W., and Gao, Y. (2015). Interactive effects of social adversity and respiratory sinus arrhythmia activity on reactive and proactive aggression. *Psychophysiology* 52, 1343–1350. doi: 10.1111/psyp.12473

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Psychology

ORIGINAL RESEARCH
published: 31 January 2020
doi: 10.3389/fpsyg.2019.03004

Attention Capture of Non-target Emotional Faces: An Evidence From Reward Learning

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The aim of this study was to explore whether reward learning would affect the processing of targets when an emotional stimulus was task irrelevant. In the current study, using a visual search paradigm to establish an association between emotional faces and reward, an emotional face appeared as a task-irrelevant distractor during the test after reward learning, and participants were asked to judge the orientation of a line on the face. In experiment 1, no significant difference was found between the high reward-fear distractor condition and the no reward-neutral condition, but the response times of the high reward-fear condition were significantly longer than those of the low reward-happy condition. In experiment 2, there was no significant difference in participants' performance between high reward-happy and no reward-neutral responses. In addition, response times of the low reward-fear condition wear significantly longer than those of the high reward-happy and no reward-neutral conditions. The results show that reward learning affects attention bias of task-irrelevant emotional faces even when reward is absent. Moreover, the high reward selection history is more effective in weakening the emotional advantage of the processing advantage than the low reward.

Keywords: reward learning, emotional face, task irrelevant, attentional capture, distractor

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Specialty section:
This article was submitted to
Decision Neuroscience,
a section of the journal
Frontiers in Psychology

Received: *20 February 2019*
Accepted: *18 December 2019*
Published: *31 January 2020*

Citation:
Zhou X, Du B, Wei Z and He W
(2020) Attention Capture of
Non-target Emotional Faces: An
Evidence From Reward Learning.
Front. Psychol. 10:3004.
doi: 10.3389/fpsyg.2019.03004

INTRODUCTION

Attention allocation is affected by reward through modulation of visual salience and behavioral motivation (Boehler et al., 2012; Botvinick and Braver, 2015). In recent years, some researchers have posited that after reward training, even a stimulus as the non-target can still automatically capture one's attention and thus receive priority processing (Anderson et al., 2011a,b; Awh et al., 2012).

As is known, emotional stimuli always receive priority attention as compared to non-emotional stimuli (Batty and Taylor, 2003; Vimal, 2008; Hodsoll et al., 2011; Barratt and Bundesen, 2012; Ikeda et al., 2013; Schmidt et al., 2015; Pool et al., 2016; Glickman and Lamy, 2017), with the exception of instances with a high percepetion load (Yates et al., 2010; Gupta and Srinivasan, 2015). In addition, early attention bias for negative emotion (such as fearful faces), in which people can quickly detect negative and threatening stimuli, has returned relatively consistent empirical results (Hansen and Hansen, 1988; Luo et al., 2010; Pinkham et al., 2010). This attention preferential processing facilitates us to respond quickly and appropriately to negative stimuli.

When emotional pictures are presented as task irrelevant, the presence of rewards can modulate attention resources and weaken the interference of emotional distractors on target processing (Padmala and Pessoa, 2014; Yokoyama et al., 2015; Walsh et al., 2018). Kulke et al. (2018) asked participants to complete a simple perceptual task while ignoring emotional images. One group was consistently rewarded for completing tasks quickly and accurately, whereas the other group was not rewarded for their performance. The results showed that the presence of rewards could alleviate the disruptive effect of emotions on the processing target (Padmala and Pessoa, 2014; Yokoyama et al., 2015; Padmala et al., 2017). It could be that the presence of rewards enables participants to alter their coping strategies from passive into active control to cope with the changes of the scene and enhance their cognitive control (Botvinick and Braver, 2015).

The association of rewards acquired from past experience can have an important impact on the attention bias. The researchers associated high values with happy faces and low values with angry faces through a reward learning phase, to see whether the reward-stimuli association would affect the processing advantage of threatening faces. The study showed that the preferential processing of anger can be modified by reward learning rather than the impact of endogenous attention during the test (Yao et al., 2013). Reward-modulation effects learned through value association impair early visual perception and hence attention allocation to angry faces. In the later stages of emotional processing, participants employed more cognitive resources to process reward history (Chen and Wei, 2019).

We note that in studies of reward-emotional attention processing, emotional faces appeared as targets during training after the reward is learned, whereas previous studies showed that the combination of reward and goal facilitates target processing (Fan et al., 2014). However, it is still unknown whether reward has an effect on the attention capture of non-target emotional faces when the reward information is absent. In addition, in some studies, reward information (reward cues or feedback) and stimuli were presented at the same trial (Bijleveld et al., 2010; Hickey et al., 2011; Wei et al., 2014, 2015), which inevitably activated reward expectation or reaction motivation of individuals. Unlike the cue paradigm or feedback paradigm, reward learning has a strong shaping effect on individual behavior and mental processing (Libera and Chelazzi, 2014), which can result in the avoidance of the influence of reward expectation and motivation on attention processing (Hammerschmidt et al., 2018). Therefore, our study established an association between emotional faces and rewards through reward learning, and explored whether the reward learning would affect the processing of targets when the emotional stimuli appeared as task-irrelevant distractors and also when reward information is absent during the testing phase. The study consists of two experiments. Experiment 1 was designed to investigate the processing characteristics of low reward-happy and high reward-fearful faces during the test phase after establishing a learning association. Considering the different reward values, their association had different effects on attention selection (Anderson et al., 2011a). Experiment 2 was aimed at investigating the attention processing of high reward-happy and low reward-fear conditions during test phase after reward associations were established. Based on previous studies regarding the relationship between reward and emotional processing, we hypothesized that, after the reward learning, the interference effect of the emotional face would be alleviated in the testing phase when it was presented to be task irrelevant, especially in cases involving a fearful face.

EXPERIMENT 1

Methods

Participants

Twenty-two students (14 female, 8 male; mean age, 20.36 years; age range, 18–24 years) from Liaoning Normal University participated in the experiment. They were all right handed and had either normal or corrected-to-normal vision. The research protocol was approved by the Research Center of Brain and Cognitive Neuroscience, Liaoning Normal University Institutional Review Board, and informed consent forms were signed by all participants. Our rationale for sample size was based on previous studies (e.g., Jahfari and Theeuwes, 2016) and obtained in G-power by setting the partial η^2 as 0.25, α as 0.05, and power $(1 - \beta)$ as 0.8.

Stimuli

Pictures depicting emotions were chosen from the China Facial Affective Picture System (Huang et al., 2011). Three types of emotion faces were used: happy (N = 6; male 3, female 3); fearful (N = 6; male 3, female 3); and neutral (N = 6; male 3, female 3). To ensure the consistency of material stimuli, we matched the arousal and the facial attractiveness. Twelve participants assessed the valence, arousal, and attractiveness of the emotional faces. There were significant differences in the valence of the three emotions [$F(2,11) = 141.36$, $p < 0.001$, $\eta_p^2 = 0.357$; happy (2.89 ± 0.45), neutral (4.52 ± 0.32), and fearful (6.32 ± 0.62)]. Happy and fearful faces used here were matched on their arousal [mean (M) ± SD, happy (5.33 ± 0.21), fear (5.82 ± 0.35), $t_{12} = 2.97$, $p = 0.94$], the arousal of neutral faces was 3.72 ± 0.32. There was no significant difference in facial attractiveness [$F(2,11) = 128.68$, $p = 0.69$, $\eta_p^2 = 0.025$; happy (4.23 ± 0.35), neutral (4.12 ± 0.32), fearful (4.08 ± 0.44)]. Luminance was controlled for in the emotional faces using a unified template in Photoshop CS6, and we added line segments in different directions (vertical, horizontal, or oblique) between the eyebrows.

Procedure

In an electromagnetic-shielded room, the participants were seated comfortably approximately 80 cm away from a 17-inch cathode-ray tube screen display. They performed a visual search task adapted from Anderson et al. (2011a,b). The time course for the reward learning and testing phases is shown in **Figures 1A,B**. During both the training and test phases, the fixation display included a black fixation cross (0.5° × 0.5° visual angle) presented in the center of the display against a gray background, and the search display consisted of the fixation cross surrounded by six emotional faces (3.58° × 3.58° visual angle of each face). The diameter of the emotional stimulation was 10.7°.

Training Phase

In the training phase, a baseline block of 120 trials was given to the participants. During the baseline, emotional faces (happy or fearful) were presented as background (there were six faces, one of which was happy or fearful), and one of the neutral faces had a horizontal or vertical line between the eyebrows. The participants were asked to ignore the face and judge the line orientation. The rewarding phase had six learning blocks (540 trials). Six emotional faces (one was a fearful or happy face; the other are neutral faces) were presented in the search display. Furthermore, the target for each trial was a unique emotional face with either a vertical or horizontal black line between the eyebrows (**Figure 1C**). The participants were required to press the F or J key as quickly as possible when judging whether the line orientation between the eyebrows was horizontal or vertical. After a correct reaction by the participants, the corresponding reward feedback and total score appeared on the screen.

Fearful faces (high reward) were followed by "+100 points" feedback at 80% percent, and the remainder was "+20 points." For happy faces (low reward), the percentages were reversed. It should be pointed out that 500 points were the equivalent of 1 Chinese Yuan Renminbi. Participants were clearly informed that their additional monetary reward was determined by the total points they earned.

Test Phase

After finishing the training phase and resting for an hour, all participants completed a second visual search task in which they identified the orientation of a line between the eyebrows. During the test phase, the search display consisted of a fearful face or a happy face among neutral faces, and the target was

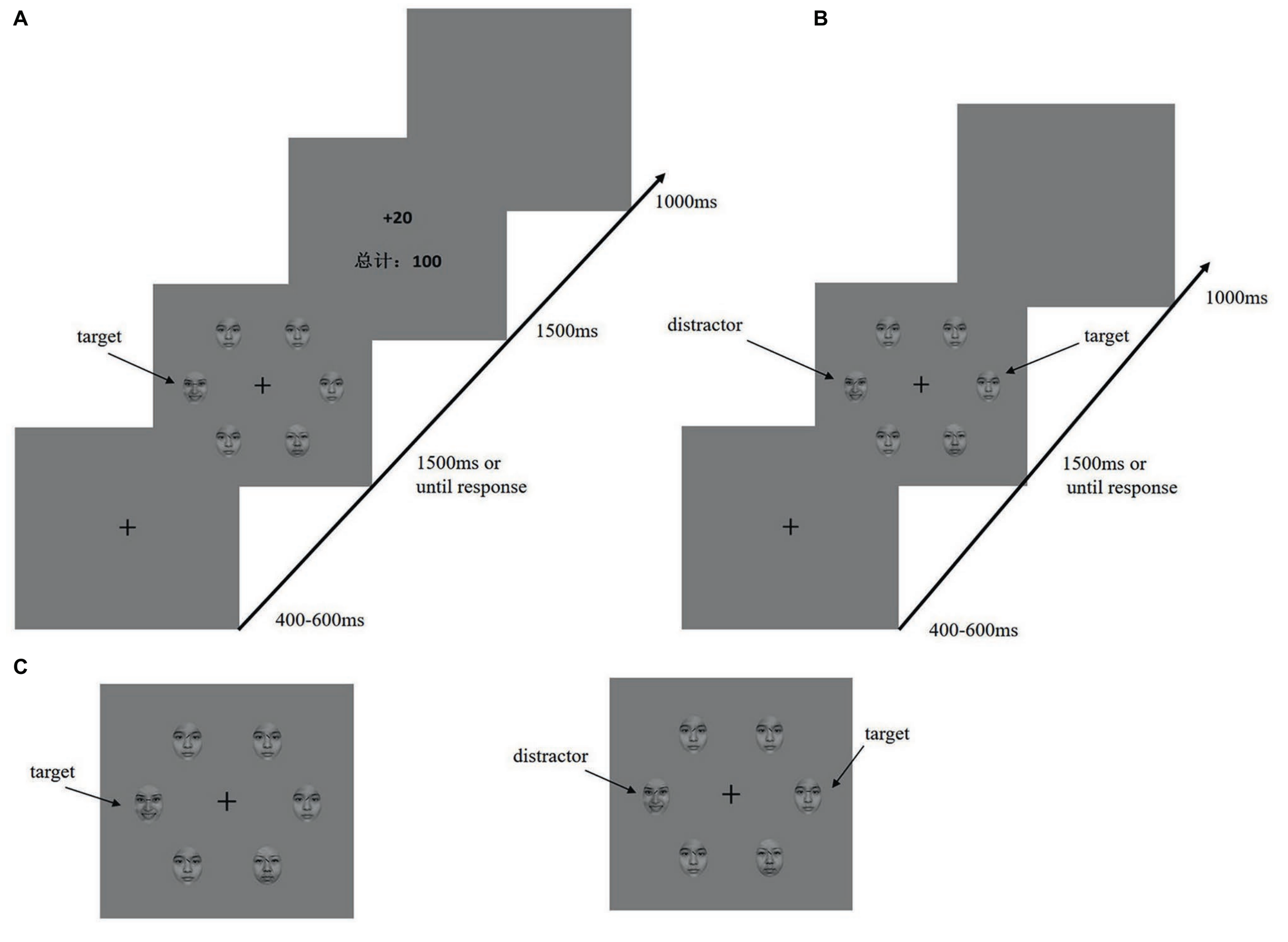

FIGURE 1 | Sequence of trial events. **(A)** Target of training phase was defined by the line of eyebrows on the emotional faces (happy or fearful, only one was present on each trial). Participants must report the line segment inside of the emotion target (horizontal or vertical). Only the correct response will be rewarded. **(B)** Test phase; the target was defined as a neutral-emotion face with a horizontal or vertical line. The distractor was formerly rewarded emotion face. **(C)** To the left is the target of the training phase; to the right is the target and distractor of the testing phase.

defined as the horizontal or vertical line between the eyebrows (**Figure 1C**). The participants were told that the experimental trials would not contain a reward. For the test phase, each trial began with a fixed display (400–600 ms). Next, a search display lasted 1,500 ms until the participant responded. An interval appeared after the response. The test contained no reward feedback, only a blank screen lasting 1,000 ms. The test contained one practice block (12 trials) and six formal blocks (each 160 trials). In the test phase, to ensure that the participants could observe the attention capture effect, 50% of the trials were no-reward distractor stimuli. In the remaining 50% of the trials, 25% were high-reward disturbance stimuli, and the remaining 25% were low-reward distractors.

Results

Training Results

During the training, we found that the mean accuracy (ACC) for high reward-fear [$t(19) = -5.03$, $p < 0.001$, Cohen's $d = 0.39$] and low reward-happy [$t(19) = -8.19$, $p < 0.001$, Cohen's $d = 1.72$] conditions increased as compared to baseline (baseline: fear 89.31 ± 7.89, happy 86.89 ± 6.39, neutral 90.79 ± 5.93; reward training: high reward-fear 97.25 ± 2.81, low reward-happy 97.49 ± 2.63, neutral 95.98 ± 3.93). A repeated-measures ANOVA showed that ACC differed significantly among these three conditions [$F(2,38) = 4.04$, $p = 0.025$, $\eta_p^2 = 0.16$]. There was no significant difference between high reward-fear and low reward-happy conditions [$t(19) = -0.79$, $p = 0.44$, Cohen's $d = 0.03$]. In addition, the difference between low reward-happy and neutral did not reach significance [$t(19) = 1.96$, $p = 0.06$, Cohen's $d = 0.03$]. However, there was a significant difference between low reward-happy and neutral [$t(19) = 2.21$, $p = 0.04$, Cohen's $d = 0.31$]. The results of the response times (RTs) between reward learning and baseline were not significantly different (baseline: fear 1257.46 ± 78.71 ms, happy 1251.40 ± 88.05 ms, neutral 1266.93 ± 80.73 ms; reward training: high reward-fear, 1262.20 ± 133.1 ms, low reward-happy 1254.57 ± 113.41 ms, neutral 1304.96 ± 105 ms). The training phase data are shown in **Figure 2**.

Test Results

Next, we examined how reward experiences affected the face section of the test. A repeated-measures ANOVA on accuracy of reward distractor types was used (high reward-fear 94.07 ± 3.23, low reward-happy 94.89 ± 2.34, neutral 94.17 ± 3.52). There was no main effect on distractor [$F(2,38) = 2.27$, $p = 0.11$, $\eta_p^2 = 0.09$]. A repeated-measures ANOVA showed that RTs differed significantly among distractor conditions (high reward-fear 1317.49 ± 87.53 ms, low reward-happy 1256.01 ± 65.83 ms, no distractors 1304.58 ± 77.51 ms) [$F(2,38) = 10.44$, $p < 0.001$, $\eta_p^2 = 0.54$]. A high reward-fear distractor slowed RTs relative to low-happy [$t(19) = 3.77$, $p = 0.001$, Cohen's $d = 0.78$]. The test phase data are shown in **Figure 3**.

EXPERIMENT 2

Experiment 1 provided evidence that emotional faces interfered with target processing after reward learning. However, that part of the experiment trained only the low-happy and the high-fear emotions, and not the high-happy and low-fear emotions. In addition, high rewards can give individuals a positive experience, but we wanted to discover whether the combination of high reward-positive emotion generates a stronger attention bias than the negative emotion-low reward. Therefore, in experiment 2, we used the happy-high and fear-low reward combinations in the reward learning phase. The sample size obtained was the same as experiment 1.

Methods

Participants

Twenty students (12 female 8 male; mean age, 21.8 years; age range, 18–25 years) from Liaoning Normal University participated in this experiment. They were all right handed and had either normal or corrected-to-normal vision. The research protocol was approved by the Brain and Cognitive Neuroscience Research Center, Liaoning Normal University Institutional Review Board, and informed consent forms were signed by all participants.

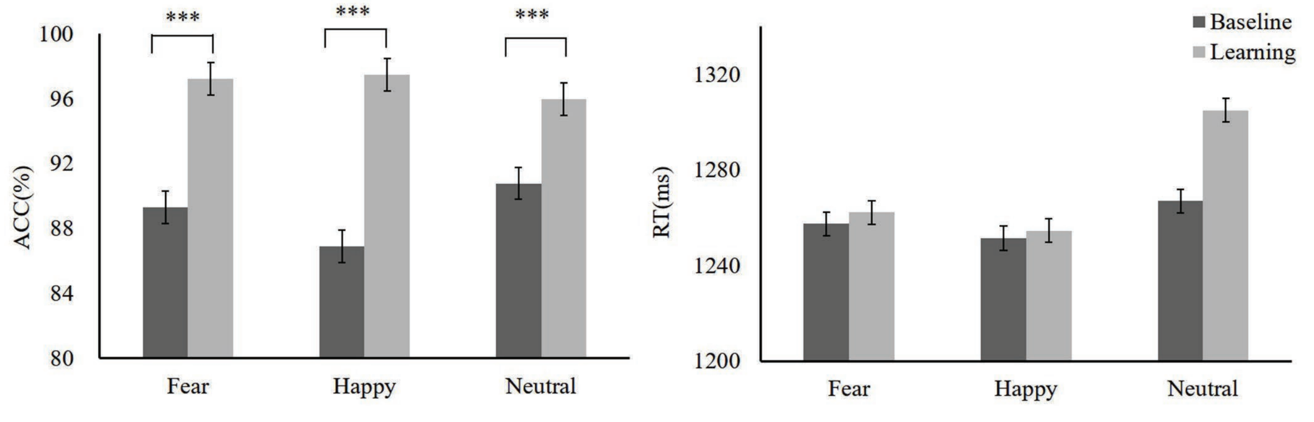

FIGURE 2 | Mean accuracy (ACC) and response times (RTs) of training phase, baseline, and training. Mean ACC to high reward-fear, low reward-happy, and no reward-neutral increased compared with baseline (experiment 1). ***$p < 0.001$.

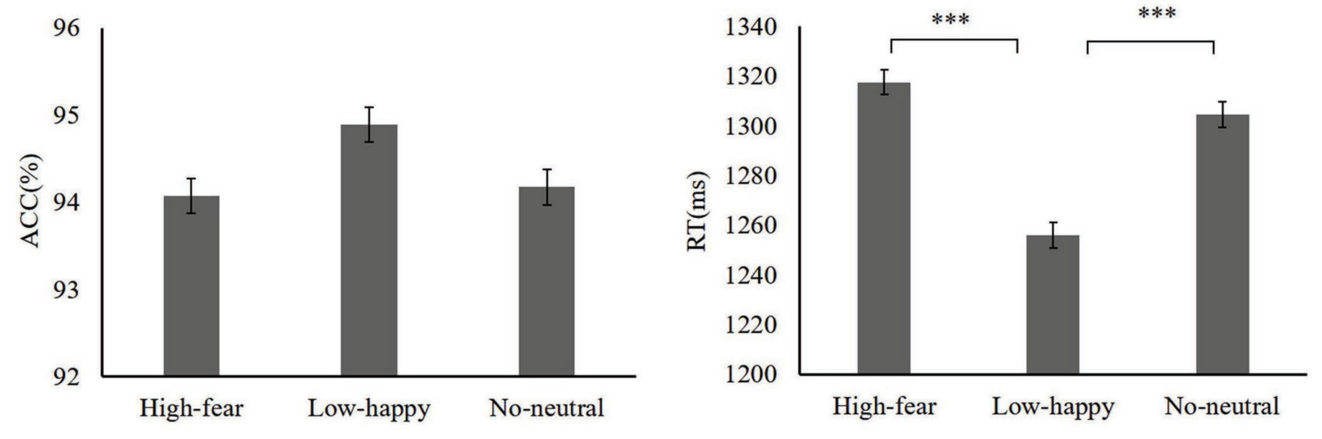

FIGURE 3 | Mean ACC and RTs in different reward distractor conditions (experiment 1). $^{***}p < 0.001$.

Stimulus, Procedure, and Data Analysis

The stimuli, apparatus, procedure, and analysis were identical to those of experiment 1 with the following exceptions. During training, participants were asked to press F or J as quickly as possible whenever they saw a fearful or happy face with either a vertical or horizontal line. Then, a visual feedback informed the participant of the reward earned in that trial, as well as about the total reward accumulated across the trial. Fearful faces low reward were followed by "+20 points" in 80%; the remainder was "+100 points." For happy faces (high reward), the percentage was reversed.

Results

Training Results

During the training, we compared baseline with training. Participants showed high ACC to high reward-happy [$t(19) = -4.18$, $p = 0.001$, Cohen's $d = 0.96$] and low reward-fear [$t(19) = -4.61$, $p < 0.001$, Cohen's $d = 1.06$] compared with the baseline (baseline: fear 88.63 ± 3.35, happy 92.79 ± 2.73, neutral 92.58 ± 3.59; reward training: low reward-fear 96.79 ± 2.15, high reward-happy 96.94 ± 4.38, neutral 98.1 ± 3.24). There was no significant difference in RTs between reward training and baseline except in high reward-happy compared with happy [baseline: fear 1207.67 ± 65.25 ms, happy 1184.82 ± 121.8 ms, neutral 1175.96 ± 73.53 ms; reward training: low reward-fear 1251.11 ± 89.92 ms, high reward-happy 1246.49 ± 94.57 ms, neutral 1149.89 ± 114.83 ms; $t(19) = -2.26$, $p = 0.016$, Cohen's $d = 0.61$]. A repeated-measures ANOVA showed that ACCs among rewards are significantly different [$F(2,38) = 4.32$, $p = 0.021$, $\eta_p^2 = 0.19$]. Low reward fear ACC is lower than neutral [$t(19) = -2.5$, $p = 0.022$, Cohen's $d = 0.58$], and high-reward happy is lower than neutral [$t(19) = -2.09$, $p = 0.05$, Cohen's $d = 0.48$]. There is also a significant difference in RTs for reward types after reward learning [$F(2,38) = 16.18$, $p < 0.001$, $\eta_p^2 = 0.47$]. The training phase data are shown in **Figure 4**.

Test Results

We wanted to know the impact of previous learning on performance when performance was not predictive of reward. An ANOVA was conducted on the ACC with reward condition. The results showed that there was no difference of reward [$F(2,38) = 1.07$, $p = 0.19$, $\eta_p^2 = 0.04$; high reward-happy 97.11 ± 7.54, low reward-fear 96.61 ± 5.47, neutral 97.33 ± 3.41]. The analysis of ANOVA on the RT indicated that there are significant differences between reward types [$F(2,38) = 18.76$, $p < 0.001$, $\eta_p^2 = 0.14$; high reward-happy 1189.84 ± 118.12 ms, low reward-fear 1253.07 ± 120.40 ms, no distractors 1174.35 ± 97.67 ms]. Paired comparisons showed significant differences between high reward-happy and low reward-fear ($p = 0.001$). There was a significant difference between low reward-fear and no reward-neutral ($p = 0.001$), but there was no difference between high reward-happy and no reward-neutral. The test phase data are shown in **Figure 5**.

Between-Experiments Comparison

The ACC data were evaluated with a 2(Reward: high and low) × 2(Emotion: fearful and happy) repeated-measures ANOVA. The main effects of reward ($F < 1$) and emotion ($F < 1$) were not significant, and the interaction of reward × emotion was also not significant [$F = 2.87$, $p = 0.109$, $\eta_p^2 = 0.14$].

We also evaluated the RT data according to a 2(Reward: high and low) × 2(Emotion: fear and happy) repeated-measures ANOVA. The main effect of reward was not significant ($F < 1$), and the mean RTs of high reward and low reward were the same. The main effect of the emotion was significant [$F(1,36) = 28.9$, $p < 0.001$], and the mean RT of the fearful face distractor was slower than that for the happy face. Critically, a significant Reward × Emotion interaction was detected [$F(1,36) = 5.31$, $p = 0.034$, $\eta_p^2 = 0.24$]. The results of simple effect analysis showed that there was a significant difference in the fearful face distractor between high and low reward conditions [$F(1,36) = 5.73$, $p = 0.029$]. High reward is slower than low reward. Moreover, there were significant differences in emotion faces [$F(1,36) = 14.61$, $p = 0.001$]. The fearful distractors (1317.49 ms) were longer than the happy distractors (1189.84 ms) in the high-reward condition; there was no such significant difference in the low-reward condition ($F < 1$). The group comparison data are shown in **Figure 6**.

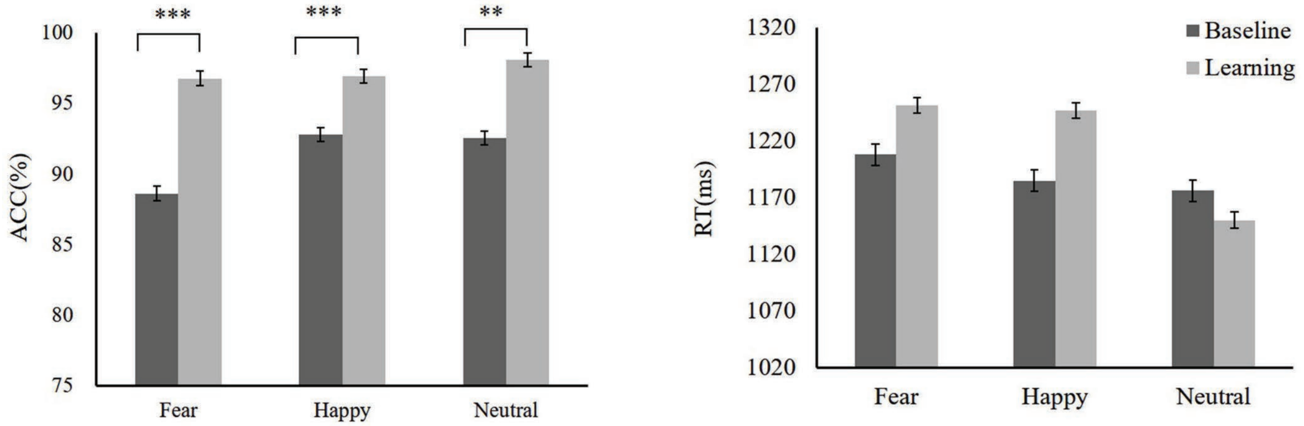

FIGURE 4 | Mean ACC and RTs of training phase, baseline, and training. Mean ACC to low reward-fear, high reward-happy, and no0020reward-neutral increased compared with baseline (experiment 2). **$p < 0.01$; ***$p < 0.001$.

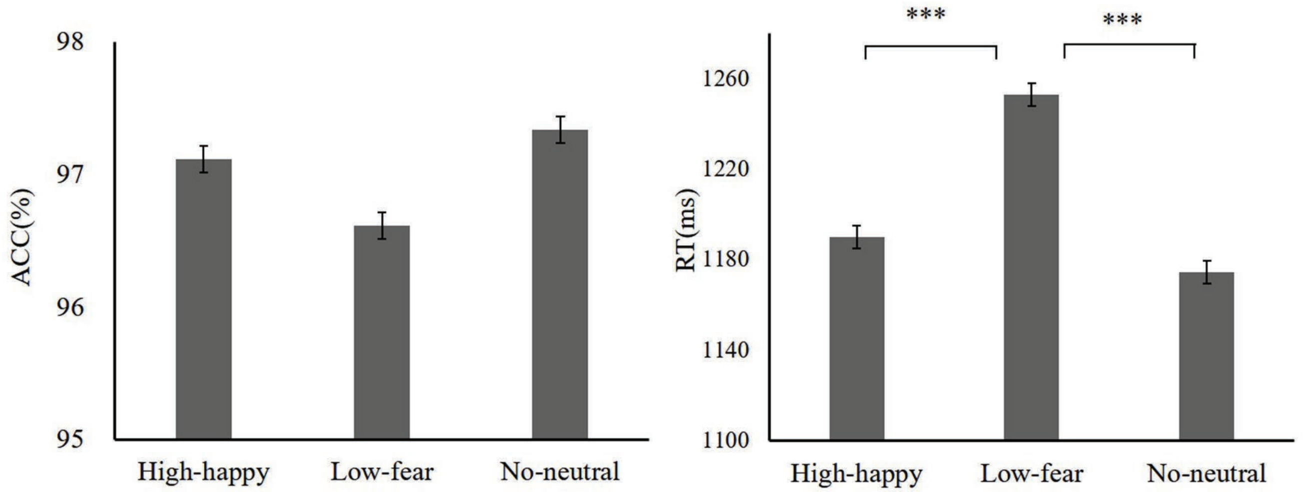

FIGURE 5 | Mean ACC and RTs in different reward distractor conditions (experiment 2). ***$p < 0.001$.

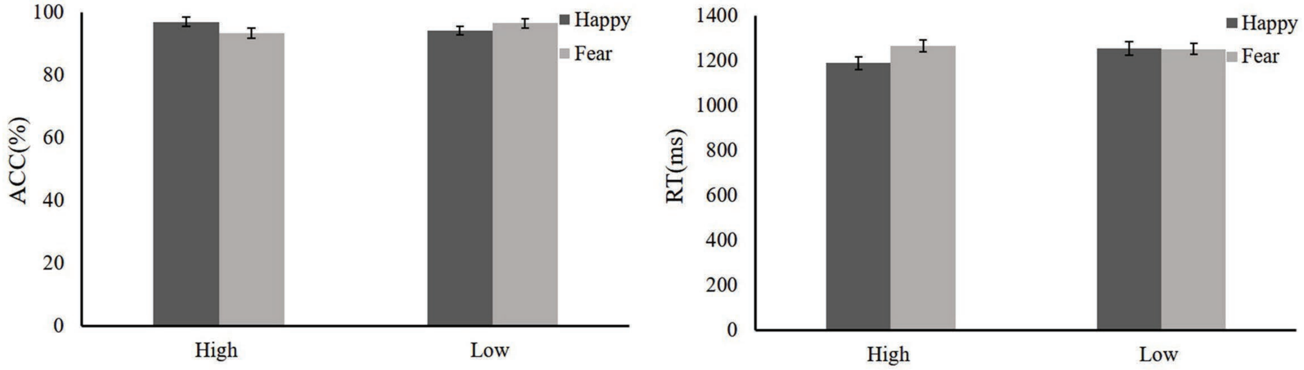

FIGURE 6 | Mean ACC and RTs in different reward distractor and emotions.

DISCUSSION

In the current study, we used the reward learning paradigm to investigate the effects of reward learning on attention capture of non-target emotional faces. During the training phase, the fearful and happy faces were connected with different rewards (high vs. low rewards). The participants then completed visual search tasks in the testing phase without any reward feedback, in which emotional faces trained in reward learning were presented as non-target distractors. The results showed that after the reward training, the ACC of the emotional faces was significantly improved compared with the baseline. During the test phase, no significant difference was found between high reward-fear and no reward-neutral conditions, or between high reward-happy and no reward-neutral conditions. The RTs were shorter in the low reward-happy condition than in the high reward-fear and no reward-neutral conditions. In addition, the RT was longer for low reward-fear versus high reward-happy and no reward-neutral conditions. The results suggest that the reward selection history perhaps changed the attentional selection of non-target emotional faces after high-reward learning.

Reward has a strong effect on cognition and can allocate a mass of cognitive resources to reward-related stimuli (Wei et al., 2014). During reward training, fearful and happy faces were presented as the target background, and the attention resources of the participants could be biased toward the facial background (Langton et al., 2008; Wentura et al., 2011). During such training, participants may have implicitly learned an association between the emotional faces and the rewards. Reward feedback enhances the response motivation and improves the performance of target processing (Anderson et al., 2011b; Anderson, 2016).

In the test of experiment 1, no difference was confirmed between the high reward-fear distractor condition and the no reward-neutral condition, but the RTs of the high reward-fear condition were longer than those of the low reward-happy condition. It is well known that threatening stimuli (e.g., fear, anger) could capture the individuals' attention, despite the fact that they were irrelevant to the current goal (Batty and Taylor, 2003; Barratt and Bundesen, 2012; Ikeda et al., 2013; Bucker et al., 2014). However, the current results suggest that processing a fearful face does not generate attention disengagement difficulties. Recent studies regarding reward and emotional processing found that the processing advantage of irrelevant negative stimuli was impaired under reward conditions (Schettino et al., 2013; Padmala and Pessoa, 2014; Yokoyama et al., 2015). In Padmala and Pessoa's (2014) study, however, rewards and tasks were presented in the same stimulus sequence. In our study, reward feedback did not appear during the test. Results still show that the value association between high reward and fearful faces still weakens the processing advantage of fearful faces when the reward feedback is absent. Because of the high reward-fear association acquired, the participants may have adopted an active strategy, which weakens the distraction of irrelevant stimuli on the target searching. It further showed that reward training can effectively regulate the processing of non-target fearful faces, and that the reward-learning effect persisted even when the reward does not appear.

In the test of experiment 2, there was no difference in participants' performance between high reward-happy and no reward-neutral conditions. In addition, the RTs of the low reward-fear condition were longer than those of the high reward-happy and no reward-neutral. It is rather easy to produce perceptual priming with positive emotions in social life situations, which is very common and familiar (Öhman et al., 2001). After the learning between happy face and high reward, it may enhance positive emotional experience, causing the participant to react faster to the happy face distractor. Unlike previous studies, the fearful face was not affected by low-reward learning and still showed a negative processing bias (Itthipuripat et al., 2015; Yokoyama et al., 2015; Bourgeois et al., 2017). We supposed that this may be due to the different task paradigms used and task-irrelevant stimulate previously associated with a small reward shows weaker impact than that previously associated with a larger reward (Anderson et al., 2011a). Moreover, in the study by Yokoyama et al. (2015), tasks were relatively easy with less interference. In the current study, the target search is more difficult because of a lot of task-irrelevant stimulate.

Previous studies concerning reward learning showed that different rewards have disparate effects on attention processing after reward learning. More specifically, task-irrelevant distractor previously associated with a large reward slows visual search more than an equally salient distractor previously associated with a small reward (Anderson et al., 2011a,b; Anderson, 2013). Compared with low reward, a high-reward selection experience could alleviate the disturbance effect introduced by a non-target emotional face and promote the target recognition; this finding seems to be inconsistent with the results of previous studies (Padmala and Pessoa, 2014; Yokoyama et al., 2015). On the whole, on the one hand, individuals may reallocate more cognitive resources to evaluate high-reward selection history during the decision-making stage of the emotional processing (Chen and Wei, 2019). On the other hand, the difference between the participants in experiment 1 and experiment 2 may also lead to this result. The reward learning weakens the processing advantage of the fearful face. However, the high reward-happy faces were less likely to interfere with the goal, probably because positive emotion is more common in real life.

Previous research regarding this issue usually presented rewards and goal tasks sequentially. Such a paradigm setting would increase the motivation of participants. The present study associated rewards with emotional faces in an independent training phase. During the testing, reward-associated stimuli appeared to be task irrelevant, and the reward effect can be observed indirectly. In addition, the current study used the China Facial Affective Picture System to study the emotion processing in a Chinese cultural context. The limitation is that this study chose only two types of emotional faces (happy and fearful). Thus, the discussion of how rewards influence emotional processing is simplified. Owing to the complex nature of emotional stimuli and the difficulty of the task, the reward-learning effect may be weakened. Future research will explore the impact of reward learning on other emotions, thereby appropriately reducing the difficulty of the task.

CONCLUSION

The current study investigated the impact of reward learning on emotional attentional capture and provided evidence for relationships between reward learning and emotional faces. The results showed that RTs for high reward-emotional faces distracters are faster than those for low reward-emotional faces. Furthermore, no significant difference was confirmed between the high reward-fear distractor condition and the no reward-neutral condition. We speculate that reward learning affects the attention bias of task-irrelevant emotional faces even when the reward is absent. Furthermore, reward selection history influences the attention bias of emotional faces, in which emotional faces are connected to high reward. Specifically, the attention advantages of fearful faces were regulated by high reward.

DATA AVAILABILITY STATEMENT

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 "Brain and Cognitive Neuroscience Research Centre, Liaoning Normal 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 "Liaoning Normal University Institutional Review Board."

AUTHOR CONTRIBUTIONS

XZ and ZW designed the experiment. BD collected the data. XZ analyzed relevant data and wrote the manuscript. WH revised the paper and contributed to the interpretation of the data for the work.

FUNDING

The work was supported by the National Natural Science Foundation of China (Grant No. 81601166).

REFERENCES

Anderson, B., Laurent, P., and Yantis, S. (2011b). Value-driven attentional capture. *Proc. Natl. Acad. Sci. USA* 108, 10367–10371. doi: 10.1073/pnas.1104047108

Anderson, B. A. (2013). A value-driven mechanism of attentional selection. *J. Vis.* 13:7. doi: 10.1167/13.3.7

Anderson, B. A. (2016). The attention habit: how reward learning shapes attentional selection. *Ann. N. Y. Acad. Sci.* 1369, 24–39. doi: 10.1111/nyas.12957

Anderson, B. A., Laurent, P. A., and Yantis, S. (2011a). Learned value magnifies salience-based attentional capture. *PLoS One* 6:e27926. doi: 10.1371/journal.pone.0027926

Awh, E., Belopolsky, A. V., and Theeuwes, J. (2012). Top-down versus bottom-up attentional control: a failed theoretical dichotomy. *Trends Cogn. Sci.* 16, 437–443. doi: 10.1016/j.tics.2012.06.010

Barratt, D., and Bundesen, C. (2012). Attentional capture by emotional faces is contingent on attentional control settings. *Cognit. Emot.* 26, 1223–1237. doi: 10.1080/02699931.2011.645279

Batty, M., and Taylor, M. J. (2003). Early processing of the six basic facial emotional expressions. *Cogn. Brain Res.* 17, 613–620. doi: 10.1016/S0926-6410(03)00174-5

Bijleveld, E., Custers, R., and Aarts, H. (2010). Unconscious reward cues increase invested effort, but do not change speed-accuracy tradeoffs. *Cognition* 115, 330–335. doi: 10.1016/j.cognition.2009.12.012

Boehler, C. N., Hopf, J. M., Stoppel, C. M., and Krebs, R. M. (2012). Motivating inhibition - reward prospect speeds up response cancellation. *Cognition* 125, 498–503. doi: 10.1016/j.cognition.2012.07.018

Botvinick, M., and Braver, T. (2015). Motivation and cognitive control: from behavior to neural mechanism. *Annu. Rev. Psychol.* 66, 83–113. doi: 10.1146/annurev-psych-010814-015044

Bourgeois, A., Neveu, R., Bayle, D. J., and Vuilleumier, P. (2017). How does reward compete with goal-directed and stimulus-driven shifts of attention? *Cognit. Emot.* 31, 109–118. doi: 10.1080/02699931.2015.1085366

Bucker, B., Belopolsky, A. V., and Theeuwes, J. (2014). Distractors that signal reward attract the eyes. *Vis. Cogn.* 23, 1–24. doi: 10.1080/13506285.2014.980483

Chen, N., and Wei, P. (2019). Reward association alters brain responses to emotional stimuli: ERP evidence. *Int. J. Psychophysiol.* 135, 21–32. doi: 10.1016/j.ijpsycho.2018.11.001

Fan, L., Qi, S., Guo, R., Huang, B., and Yang, D. (2014). Toward understanding the role of reward in attentional selection. *Adv. Psychol. Sci.* 22:1573. doi: 10.3724/SP.J.1042.2014.01573

Glickman, M., and Lamy, D. (2017). Attentional capture by irrelevant emotional distractor faces is contingent on implicit attentional settings. *Cognit. Emot.* 9931, 1–12. doi: 10.1080/02699931.2017.1301883

Gupta, R., and Srinivasan, N. (2015). Only irrelevant sad but not happy faces are inhibited under high perceptual load. *Cognit. Emot.* 29, 747–754. doi: 10.1080/02699931.2014.933735

Hammerschmidt, W., Kagan, I., Kulke, L., and Schacht, A. (2018). Implicit reward associations impact face processing: time-resolved evidence from event-related brain potentials and pupil dilations. *NeuroImage* 179, 557–569. doi: 10.1016/j.neuroimage.2018.06.055

Hansen, C. H., and Hansen, R. D. (1988). Finding the face in the crowd: an anger superiority effect. *J. Pers. Soc. Psychol.* 54, 917–924. doi: 10.1037/0022-3514.54.6.917

Hickey, C., Chelazzi, L., and Theeuwes, J. (2011). Reward has a residual impact on target selection in visual search, but not on the suppression of distractors. *Vis. Cogn.* 19, 117–128. doi: 10.1080/13506285.2010.503946

Hodsoll, S., Viding, E., and Lavie, N. (2011). Attentional capture by irrelevant emotional distractor faces. *Emotion* 11, 346–353. doi: 10.1037/a0022771

Huang, Y., Gong, X., Wang, Y., and Luo, Y. (2011). Revision of the Chinese facial affective picture system. *Chin. Ment. Health J.* 25, 40–46. doi: 10.3969/j.issn.1000-6729.2011.01.011

Ikeda, K., Sugiura, A., and Hasegawa, T. (2013). Fearful faces grab attention in the absence of late affective cortical responses. *Psychophysiology* 50, 60–69. doi: 10.1111/j.1469-8986.2012.01478.x

Itthipuripat, S., Cha, K., Rangsipat, N., and Serences, J. T. (2015). Value-based attentional capture influences context-dependent decision-making. *J. Neurophysiol.* 114, 560–569. doi: 10.1152/jn.00343.2015

Jahfari, S., and Theeuwes, J. (2016). Sensitivity to value-driven attention is predicted by how we learn from value. *Psychon. Bull. Rev.* 24, 408–415. doi: 10.3758/s13423-016-1106-6

Kulke, L., Bayer, M., Grimm, A., Schacht, A., Anderson, B. A., Rossi, V., et al. (2018). Motivation enhances control of positive and negative emotional distractions. *Adv. Psychol. Sci.* 26, 1556–1562. doi: 10.3758/s13423-017-1414-5

Langton, S. R. H., Law, A. S., Burton, A. M., and Schweinberger, S. R. (2008). Attention capture by faces. *Cognition* 107, 330–342. doi: 10.1016/j.cognition.2007.07.012

Libera, C. D., and Chelazzi, L. (2014). Visual selective attention and the effects of monetary rewards. *Psychol. Sci.* 17, 222–227. doi: 10.1111/j.1467-9280.2006.01689.x

Luo, W., Feng, W., He, W., Wang, N. Y., and Luo, Y. J. (2010). Three stages of facial expression processing: ERP study with rapid serial visual presentation. *NeuroImage* 49, 1857–1867. doi: 10.1016/j.neuroimage.2009.09.018

Öhman, A., Lundqvist, D., Esteves, F., and Ohman, A. (2001). The face in the crowd revisited: a threat advantage with schematic stimuli. *J. Pers. Soc. Psychol.* 80, 381–396. doi: 10.1037/0022-3514.80.3.381

Padmala, S., and Pessoa, L. (2014). Motivation versus aversive processing during perception. *Emotion* 14, 450–454. doi: 10.1037/a0036112

Padmala, S., Sirbu, M., and Pessoa, L. (2017). Potential reward reduces the adverse impact of negative distractor stimuli. *Soc. Cogn. Affect. Neurosci.* 12, 1402–1413. doi: 10.1093/scan/nsx067

Pinkham, A. E., Griffin, M., Baron, R., Sasson, N. J., and Gur, R. C. (2010). The face in the crowd effect: anger superiority when using real faces and multiple identities. *Emotion* 10, 141–146. doi: 10.1037/a0017387

Pool, E., Brosch, T., Delplanque, S., and Sander, D. (2016). Attentional bias for positive emotional stimuli: a meta-analytic investigation. *Psychol. Bull.* 142, 79–106. doi: 10.1037/bul0000026

Schettino, A., Loeys, T., and Pourtois, G. (2013). No prior entry for threat-related faces: evidence from temporal order judgments. *PLoS One* 8:e62296. doi: 10.1371/journal.pone.0062296

Schmidt, L. J., Belopolsky, A. V., and Theeuwes, J. (2015). Attentional capture by signals of threat. *Cognit. Emot.* 29, 687–694. doi: 10.1080/02699931.2014.924484

Vimal, R. L. P. (2008). Attention and emotion. *Annu. Rev. Biomed. Sci.* 10, 84–104. doi: 10.5016/1806-8774.2008.v10p84

Walsh, A. T., Carmel, D., Harper, D., and Grimshaw, G. M. (2018). Motivation enhances control of positive and negative emotional distractions. *Psychon. Bull. Rev.* 25, 1556–1562. doi: 10.3758/s13423-017-1414-5

Wei, P., Wang, D., and Ji, L. (2015). Reward expectation regulates brain responses to task-relevant and task-irrelevant emotional words: ERP evidence. *Soc. Cogn. Affect. Neurosci.* 11, 191–203. doi: 10.1093/scan/nsv097

Wei, P., Kang, G., Jinhong, D., and Chunyan, G. (2014). Monetary incentives modulate the processing of emotional facial expressions: an ERP study. *Acta Psychol. Sin.* 46, 437–449. doi: 10.3724/SP.J.1041.2014.00437

Wentura, D., Müller, P., Rothermund, K., Horstmann, G., Hodsoll, S., Viding, E., et al. (2011). Attentional capture by evaluative stimuli: gain- and loss-connoting colors boost the additional-singleton effect. *Emotion* 11, 701–707. doi: 10.1037/a0022771

Yao, S., Ding, C., Qi, S., and Yang, D. (2013). Value associations of emotional faces can modify the anger superiority effect: behavioral and electrophysiological evidence. *Soc. Cogn. Affect. Neurosci.* 9, 849–856. doi: 10.1093/scan/nst056

Yates, A., Ashwin, C., and Fox, E. (2010). Does emotion processing require attention? The effects of fear conditioning and perceptual load. *Emotion* 10, 822–830. doi: 10.1037/a0020325

Yokoyama, T., Padmala, S., and Pessoa, L. (2015). Reward learning and negative emotion during rapid attentional competition. *Front. Psychol.* 6:269. doi: 10.3389/fpsyg.2015.00269

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers
in Psychology

ORIGINAL RESEARCH
published: 03 June 2020
doi: 10.3389/fpsyg.2020.01170

Regulatory Effects of Reward Anticipation and Target on Attention Processing of Emotional Stimulation

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Studies suggest that reward and emotion are interdependent. However, there are discrepancies regarding the interaction between these variables. Some researchers speculate that the inconsistent findings may be due to different targets being used. Although reward and emotion both affect attention, it is not clear whether their impacts are independent. This study examined the impact of reward anticipation on emotion processing for different targets. A cue-target paradigm was used, and behavior and eye-tracking data were recorded in an emotion or sex recognition task under the conditions of reward and non-reward anticipation. The results showed that when the target was related to the emotional attribute of the stimulus, the reward promoted the processing target information, thereby generating reward-oriented attention. When the target was unrelated to the emotional attributes of the stimulus, the reward did not promote the processing target information, and at the same time, individuals had negative emotional biases toward the emotional faces. The results revealed that, in addition to affecting the attention to emotional faces independently, the target regulated the promotion of reward anticipation to emotional attention and attention bias toward negative stimuli.

Keywords: target, reward anticipation, emotion processing, cue-target paradigm, eye tracking

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Specialty section:
This article was submitted to Decision Neuroscience, a section of the journal Frontiers in Psychology

Received: *12 June 2019*
Accepted: *06 May 2020*
Published: *03 June 2020*

Citation:
Yao Y, Xuan Y, Wu R and Sang B (2020) Regulatory Effects of Reward Anticipation and Target on Attention Processing of Emotional Stimulation. Front. Psychol. 11:1170. doi: 10.3389/fpsyg.2020.01170

INTRODUCTION

In the process of socialization, reward is often associated with positive emotions such as pleasure and satisfaction. Both reward and emotion have affective significance, defined as either negative or positive value to the organism (Pessoa, 2009). The relationship between reward and emotion has attracted the interest of researchers. Existing studies suggest that reward and emotion impact each other. Reward induces positive emotions (Berridge and Robinson, 2003). The reward circuit in the human brain is activated when an individual imagines a pleasant scene while reading a story (Costa et al., 2010) or stares at a photograph of a lover (Aron et al., 2005). Conversely, emotion, especially negative emotion, has an impact on reward. Chen (2013) reported that depression affects the reward system: the activation of reward-related brain areas decreases when depressed patients engage in reward processing. Similarly, during a gambling task, the activation of the reward circuit is lower in college students with high depressive symptoms than in those without such symptoms (Wei, 2015).

However, there are some discrepancies among previous studies on the interaction between reward and emotion. Some studies conclude that there is no interaction between reward and emotion. For instance, Murray (2007) noted that the neural substrates for emotion and reward were partially non-overlapping. The researcher noted a distinction between reward processing and emotional reactions, with the amygdala playing a crucial role in the latter and only a conditional role in the former. In another study, the cue-target paradigm, in which subjects were asked to attend to valid and ignore invalid spatial cues and motivation was manipulated by varying the magnitude and valence of a monetary incentive expected by the subjects for performing well on the task (Engelmann and Pessoa, 2007), was used to examine the impact of different reward conditions on the identification of vocabulary attributes of the target, and no interaction was found between reward and emotion (Kaltwasser et al., 2013). However, other researchers consider that there may be an interaction between them. Wittmann et al. (2008) found that reward strengthened memory only in the context of positive emotion. The same cue-target paradigm was used to investigate the effect of reward on emotional face recognition. A significant interaction was found between reward and emotion, and only negative emotion processing and bias effects were regulated by reward (Wei et al., 2014). Researchers speculate that the key reason for the divergence in the above findings may be the different targets. The target in the research of Kaltwasser et al. (2013) was independent of the emotional valence of the material (judging whether the target was concrete or abstract), while the target in the research of Wei et al. (2014) was related to emotional valence (judging whether the target was positive or negative). Wei and Kang (2014) demonstrated that when emotion was associated with the target, the reward effect of an emotional face (the difference in reaction times <RTs> between the non-reward condition and the reward condition) was greater than that of a neutral face. When emotion was irrelevant to the target, this effect did not exist. However, due to the limited information provided by RTs (Armstrong and Olatunji, 2012), this speculation needs to be further validated at other levels (e.g., attention) by other technologies (e.g., eye movement).

Both reward (Carmona et al., 2012) and emotion (Armstrong and Olatunji, 2012) impact the attention process. For instance, studies have revealed that individuals allocate attention resources to reward-related stimuli (Anderson, 2013). Rewards help stimuli with insignificant features capture attention, even if the rewards subsequently disappear, or the stimulus is independent of the target (Wang, 2016), and when rewards are combined with distraction stimuli, the choice of goals may be hindered (Fan et al., 2014). Numerous studies have found attention biases toward negative stimuli in cognitive processes, which means that individuals detect negative, and threatening stimuli quickly (Jerónimo et al., 2017). Negative faces, especially threatening faces, attract attention, and prolong attention maintenance or reduce attention disengagement ability (Fox et al., 2001). Even if subjects are asked to ignore the emotional information contained in a face, this information still has an impact on the subjects' responses. Bias toward negative stimuli may occur in one or more phases of attention information processing, involving priming, assessment, or response preparation. However, attention is an important stage of information processing (visual: Deubel et al., 2000; auditory: Näätänen, 1990). The relationship between reward and emotion is likely to appear in the attention stage. Wei et al. (2014) claimed that reward anticipation, which involves waiting and eagerness for upcoming rewards (Oldham et al., 2018) in the reward-appetitive phase (Stavropoulos and Carver, 2014), could promote attention to target-related stimuli or attributes. When an emotional attribute of a stimulus is related to a task, it interacts with reward anticipation, which in turn affects the behavioral response of subjects. Nevertheless, this inference still needs to be supported by empirical research in the field of attention. Eye-tracking technology is commonly used to examine the characteristics of individual attention (Liu and Reichle, 2018; Scholz et al., 2018). An eye tracker can provide continuous dynamic information on subjects during cognitive processing at a high sampling rate; it is more conducive to directly measuring the time course of cognitive processing (especially attention processing) than RTs. Therefore, this study attempts to further address this problem with eye-tracking technology.

Understanding the emotional characteristics of faces is the key to social adaptation and communication skills (Trentacosta and Fine, 2010). In daily life, facial information communicates data on more than one attribute (such as sex, skin color, or expression). When reward anticipation is attached to the emotional and sex attributes of faces, what happens to the attention process? Does the relationship between reward and emotion change depending on the target? This study tried to answer these questions. As mentioned earlier, reward anticipation processing occurs during the appetitive phase of reward processing and has a strong motivational feature that plays an important role in cognitive processes (Yan et al., 2016). Since reward is usually not given in a timely manner under real experimental conditions, they likely reveal anticipation. Previous research has also found that the expectation of reward improves the preparedness of the corresponding brain regions and promotes behavioral responses to subsequent stimulation. Motivational cues bias individuals' attention resources and target-related information processing by regulating top-down cognitive processes, thereby improving behavioral performance. This study used the cue-target paradigm and eye-tracking technology to examine whether there were differences in behavioral responses and attention characteristics on different targets (emotion recognition and sex recognition) and different reward anticipation (reward and non-reward). Based on previous studies (e.g., Kaltwasser et al., 2013), this experiment predicted that only when the goal was related to the emotion, the reward could promote the processing of emotional information.

MATERIALS AND METHODS

Subjects

Twenty-five students from Zhejiang University of Technology were recruited; 6 of them were excluded because of the low average ratio of valid gaze data, which was less than 70%. Nineteen subjects (9 females, aged 18 to 21 years) had an average ratio of 89.75% for valid gaze data. All subjects had normal or corrected-to-normal visual acuity and were paid with basic rewards. This study was carried out in accordance with the recommendations of the Human Research Ethics Committee of Zhejiang University of Technology. The subjects were recruited through the campus bulletin board and provided signed, informed consent before the experiment. In addition to basic remuneration, the subjects received additional monetary awards based on their experimental performance.

Design

This study used a 2 × 2 × 2 within-subjects design (target: emotion recognition and sex recognition) × (reward anticipation: non-reward and reward) × (emotional valence: negative and positive). Dependent variables were the subjects' responses (indexed by RT and accuracy) and attention to the pictures [measured by the first fixation ratio (FFR) and fixation duration ratio (FDR)].

Drawing on the classic paradigm in eye-movement experiments, we simultaneously presented two types of stimuli on one slide to examine attention bias. Positive and negative stimuli, such as high emotional arousal stimuli, would inevitably lead to confusion in the individual emotional experience if presented at the same time. In this study, emotion was an independent variable. Therefore, neutral stimuli were added as controls. The two levels of independent variables, positive and negative emotion, were presented in positive-neutral and negative-neutral pairs.

Materials

The experimental materials (sample face pictures of different emotional valences are shown in **Figure 1**, detail information can be seen in **Supplementary Material**) included 24 neutral face pictures (calm), 12 positive face pictures (happy), and 12 negative face pictures (angry) (Descriptive statistic of valence, arousal and dominance of material see **Table 1**), selected from the Chinese Facial Affective Picture System (Wang and Luo, 2005). The sex ratio of each kind of facial expression was 1:1. There was a significant difference between the valences of the three types of face pictures ($ps < 0.05$). Additionally, there was no significant difference between positive and negative faces in arousal or dominance ($ps > 0.05$), while both positive and negative faces had significant differences from neutral faces in arousal and dominance ($ps < 0.05$).

FIGURE 1 | Sample face pictures of different emotional valences.

TABLE 1 | Descriptive statistics of valence, arousal and dominance of material ($M \pm$ SD).

Emotion	Valence	Arousal	Dominance
Neutral	4.78 ± 0.16	2.55 ± 0.27	2.92 ± 0.28
Positive	7.50 ± 0.17	5.80 ± 0.61	6.50 ± 0.43
Negative	1.97 ± 0.36	6.75 ± 0.76	5.84 ± 0.62

Instruments

A Tobii X50 telemetry eye tracker with a sampling frequency of 50 Hz was used to track and record the eye movements of the subjects. The program was presented on a 19-inch, 60-Hz cathode ray tube screen. The eye tracker consists of three parts: cameras that take high-resolution images of subjects' eyes and movement patterns, projectors that create a pattern of near-infrared light on the eye, and algorithms (machine learning, image processing, and mathematical algorithms) that are used to determine the eyes' position and gaze.

Procedure

All subjects were instructed to sit approximately 60 cm in front of the display screen and to complete the experiment independently. Based on the requirements of eye-tracking experiments, five-point calibration was used to ensure the accuracy of eye-tracking recording before the experiment started.

The procedure was written using E-prime 2.0. The subjects were asked to complete the emotion recognition task and sex recognition task separately, with corresponding instructions before each task began. The order of the tasks and the correct responses were counterbalanced between the subjects. The cue-target paradigm (Wei et al., 2014) was modified using the experimental procedure illustrated in **Figure 2**, in which the background was set to white, and the cues and fixations were set to black. Before the experimental procedure began, the subjects were informed of the experimental process and the meaning of the cues and feedback pictures. In the practice phase (shown in **Figure 2A**), each trial began with the fixation "+" (0.59° × 0.59° visual angle) in the center of the screen for 600 ms. Then, a cue "*" was presented for 500 ms. The fixation appeared again for 100 ms to reset the gaze. After that, two face pictures of different sexes and expressions were presented in pairs. In the emotion recognition task, the subjects were asked to identify the location of pictures according to emotional arousal (high or low). In the sex recognition task, they were asked to identify the location of pictures according to sex (female or male). As one of the objectives in this experiment was to measure the attention maintenance of the subject, the duration of the pictures was fixed to 1500 ms even if the subject responded. Then, the fixation appeared for another 100 ms to reset the gaze, followed by feedback for 500 ms. A gray solid circle appeared on the screen if the subject's response was correct, and a gray hollow circle appeared on the screen if it was incorrect. Moreover, since the reaction rates had individual differences, the paradigm needed to feed back the RT of subjects to determine whether they would be rewarded. The average RT of every subject in the practice phase was recorded and analyzed as a baseline.

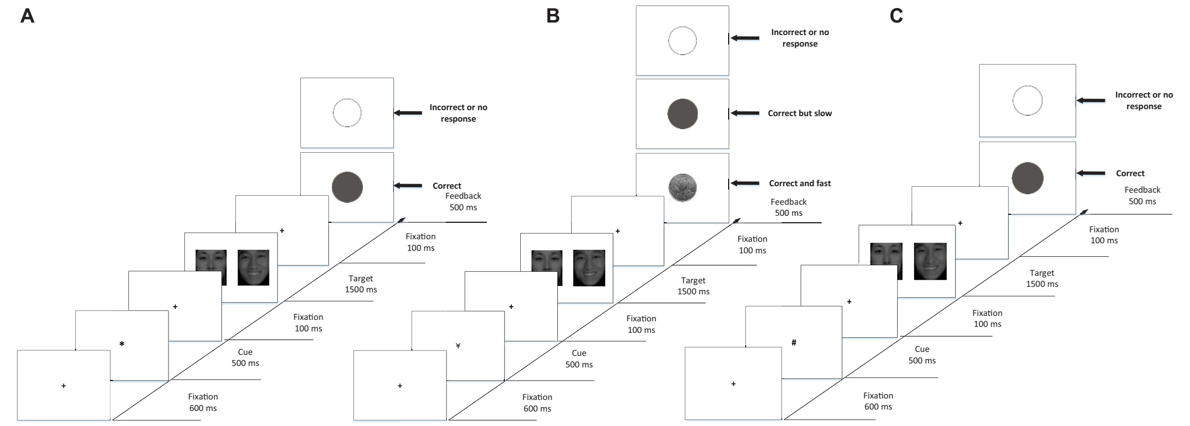

FIGURE 2 | Example displays from the cue-target paradigms used to assess reward-driven attention capture. **(A)** Practice phase with feedback. **(B)** Formal phase with reward feedback. **(C)** Formal phase with non-reward feedback. Each trial was followed by a blank intertrial interval.

The formal experiment was divided into reward trials (as shown in **Figure 2B**) and non-reward trials (as shown in **Figure 2C**). In the reward trials, "¥" was presented as a cue to represent money. The feedback varied depending on the response of the subject: if the subject responded correctly and faster than his or her baseline, a coin would be presented on the screen; if the subject reacted correctly but more slowly than his or her baseline, a gray solid circle appeared on the screen; if the subject reacted incorrectly, a gray hollow circle appeared on the screen. In non-rewarded trials, "#" was presented as a cue to represent no money. The feedback varied depending on the response of the subject: if the subject's reaction was correct, regardless of how fast the reaction, a gray solid circle appeared on the screen; if the subject's reaction was incorrect, a gray hollow circle appeared on the screen.

There were 32 trials in the practice phase, of which 16 trials were sex recognition tasks (8 reward trials and 8 non-reward trials), and 16 trials were emotion recognition tasks (8 reward trials and 8 non-reward trials). There were 128 trials in the formal phase, of which 64 trials were sex recognition tasks (32 reward trials and 32 non-reward trials), and 64 trials were emotion recognition tasks (32 reward trials and 32 non-reward trials). In the formal experiment, 8 trials with the same task (recognizing emotion or sex) were used as a block, with a total of 16 blocks. The presentation order of blocks was balanced between subjects. The cues (¥ or #) and the same categories of pictures (such as a happy male face) were presented randomly within blocks.

Data Analysis

The RTs and accuracies of the subjects in the formal experiment were recorded by E-prime 2.0. E-DataAid was used to collate the data, which were exported to SPSS 22.0 for further statistical analysis. The Bayesian factor (BF_{10}) was calculated by JASP[1] (Wu et al., 2018). JASP provides options for model comparison and data results output. We chose "compare to best model" for model comparison and "across matched models" for calculating the effect of the data. Based on Jeffreys (1961) and Wetzels and Wagenmakers (2012), the interpretation of the Bayesian factor (BF_{10}) is presented in **Table 2**.

TABLE 2 | Interpretation of Bayesian factors (BF_{10}).

Bayesian factor BF_{10}	Label
>100	Extremely significant
30–100	Very strongly significant
10–30	Strongly significant
3–10	Moderately significant
1–3	Anecdotally significant
0–1	Not significant

The eye trajectories to faces were determined by presenting positive/negative faces and neutral faces simultaneously as two areas of interest (AOIs) on one slide. The time to first fixation (TFF) and total fixation duration (TFD) data were obtained. TFF is the time point when the gaze of the subject falls on the stimulus for the first time with a latency less than 700 ms and a duration greater than 100 ms. Researchers generally use TFF to reflect subjects' facilitated attention, which belongs to the automatic processing system and is driven by stimulation. TFF reflects the processing order of a stimulus, which means that the shorter the TFF is, the earlier the AOI is noticed, and the more sensitive or alert an individual is to the stimulus (Cisler and Koster, 2010). TFD is the sum of the fixation durations of subjects to the AOI during the entire stimulus presentation process. Researchers generally use TFD to reflect an individual's difficulty with disengagement from stimulation (indicating damage to the attention control system) or attention avoidance (reflecting activation of the attention control system), which can reflect the entire cognitive processing of stimulation (Cisler and Koster, 2010).

Time to first fixation and TFD are time variables that are easily affected by individual differences. Differences in results may be caused by differences in the attention features of individuals

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[1] https://jasp-stats.org/

TABLE 3 | Descriptive statistics of accuracy and RT under different conditions (M ± SD).

		Accuracy		RT (ms)	
Target	**Reward anticipation**	**Positive**	**Negative**	**Positive**	**Negative**
Emotion	Reward	0.92 ± 0.07	0.93 ± 0.07	740.25 ± 156.85	729.19 ± 131.93
	Non-reward	0.94 ± 0.06	0.95 ± 0.05	784.56 ± 161.5	762.14 ± 127.50
Sex	Reward	0.98 ± 0.03	0.91 ± 0.08	759.47 ± 138.40	791.69 ± 153.80
	Non-reward	0.98 ± 0.03	0.91 ± 0.05	762.65 ± 118.85	794.42 ± 157.79

rather than different experimental conditions. As in previous studies (Wang and Yu, 2017), RT was transformed into the change ratio of RT to exclude the influence of individual differences on the target. We reanalyze TFF and TFD in the form of ratios to define FFR and FDR as new dependent variables. FFR is defined as the ratio of the number of trials with a quicker TFF in a positive/negative AOI to the total number of trials for the same experimental condition compared with a neutral AOI. For example, there were 32 negative-neutral reward trials in the emotion recognition task. If there were 24 trials with a quicker TFF for negative faces than for neutral faces, then the FFR in negative-neutral reward trials would be 0.75. The calculation of FDR is also based on two AOIs of positive/negative and neutral faces. FDR is defined as the ratio of the total TFD in a positive/negative AOI to the sum of TFDs in two AOIs under the same experimental conditions. For example, if the total TFD of negative faces were 16000 ms and the sum of the TFDs of negative and neutral pictures were 20000 ms in the 32 negative-neutral reward trials in the emotion recognition task, the FDR would be 0.8.

The statistical analyses we used are presented as follows. First, accuracy and RT were analyzed separately using repeated-measures ANOVA, taking target (emotion recognition and sex recognition), reward anticipation (reward and non-reward), and emotional valence (negative and positive) as factors. Regarding the target differences, we performed a separate repeated-measures ANOVA for each task with reward anticipation and emotional valence as factors. Since neutral faces and emotional faces were presented at the same time, we integrated FFR and FDR into the positive condition and negative condition, taking 0.5 as the expected value to perform a one-sample t-test. Finally, FFR and FDR as eye-tracking indexes were separately analyzed using repeated-measures ANOVA, taking reward anticipation, emotional valence, and target as factors. We also performed a separate repeated-measures ANOVA for each target with experimental reward anticipation and emotional valence as factors. Where a significant difference was found between factors, Student's t-test was used.

RESULTS

Behavioral Data

ANOVA results (descriptive statistics are reported in **Table 3**) show that the interaction between target and emotion was significant in terms of accuracy [$F(1,18) = 17.15$, $p = 0.001$, $\eta_p^2 = 0.49$, and $BF_{10} = 1083.61$] and RT [$F(1,18) = 4.97$, $p < 0.05$, $\eta_p^2 = 0.22$, $BF_{10} = 1.24$]. The simple effect test found that in the sex recognition task, there was a higher accuracy ($p < 0.05$) and a shorter RT ($p < 0.05$) under the positive condition, indicating superior processing toward positive faces, and that there was no significant difference in the emotion recognition task. The main effect of emotion on accuracy was significant [$F(1,18) = 8.75$, $p < 0.05$, $\eta_p^2 = 0.33$, and $BF_{10} = 16.46$], reflecting that accuracy under the positive condition was higher than that under the negative condition. Other main effects and interactions were not significant ($ps > 0.05$). Separate repeated-measures ANOVA results showed that in the emotion recognition task, the main effect of reward anticipation was significant [$F(1,18) = 5.18$, $p < 0.05$, $\eta_p^2 = 0.22$, and $BF_{10} = 2.67$]. This result reflects a shorter RT under the reward condition than under the non-reward condition and indicates a behavior bias toward reward. In the sex recognition task, the main effect of emotion was significant [$F(1,18) = 4.50$, $p < 0.05$, $\eta_p^2 = 0.20$, and $BF_{10} = 1.01$], manifesting as a shorter RT under the positive condition than under the negative condition. Other main effects and interactions were not significant ($ps > 0.05$).

Eye-Tracking Data

The results of the one-sample t-test (descriptive statistics are reported in **Table 4** and **Figure 3**) show that FFR was marginally significantly different under negative conditions [$t(18) = 2.06$, $p = 0.06$, $d = 0.67$, and $BF_{10} = 2.55$], indicating an attention bias toward negative faces. FDR was also significantly different under negative conditions [$t(18) = 2.58$, $p < 0.05$, $d = 0.84$, and $BF_{10} = 6.13$], suggesting that negative faces were able to hold attention longer than neutral faces. Under positive conditions, comparing FFR and FDR with 0.5, no significant difference could be asserted ($ps > 0.05$).

The ANOVA results show that the main effect of the target was significant [$F(1,18) = 18.13$, $p = 0.000$, $\eta_p^2 = 0.50$; and $BF_{10} = 10.02$] on FFR, with a lower FFR in the emotion recognition task than in the sex recognition task. The main effect of emotion was also significant [$F(1,18) = 5.82$, $p = 0.03$, $\eta_p^2 = 0.24$; and $BF_{10} = 1.03$]; the FFR of positive faces was lower than that of negative faces, which also indicated a negative bias. Other main effects and interactions were not significant ($ps > 0.05$). Separate repeated-measures ANOVA results show that in the emotion recognition task, the main effect of reward anticipation was significant [$F(1,18) = 5.37$, $p = 0.03$, $\eta_p^2 = 0.23$; and $BF_{10} = 1.89$], with a significantly lower FFR under the reward condition than under the non-reward condition. Additionally,

TABLE 4 | Descriptive statistics of FFR and FDR under different conditions ($M \pm$ SD).

		FFR		FDR	
Target	**Reward anticipation**	**Positive**	**Negative**	**Positive**	**Negative**
Emotion	Reward	0.43 ± 0.10	0.49 ± 0.03	0.55 ± 0.13	0.57 ± 0.14
	Non-reward	0.47 ± 0.07	0.53 ± 0.11	0.52 ± 0.10	0.55 ± 0.10
Sex	Reward	0.52 ± 0.11	0.51 ± 0.13	0.48 ± 0.19	0.51 ± 0.05
	Non-reward	0.53 ± 0.10	0.55 ± 0.12	0.50 ± 0.05	0.51 ± 0.06

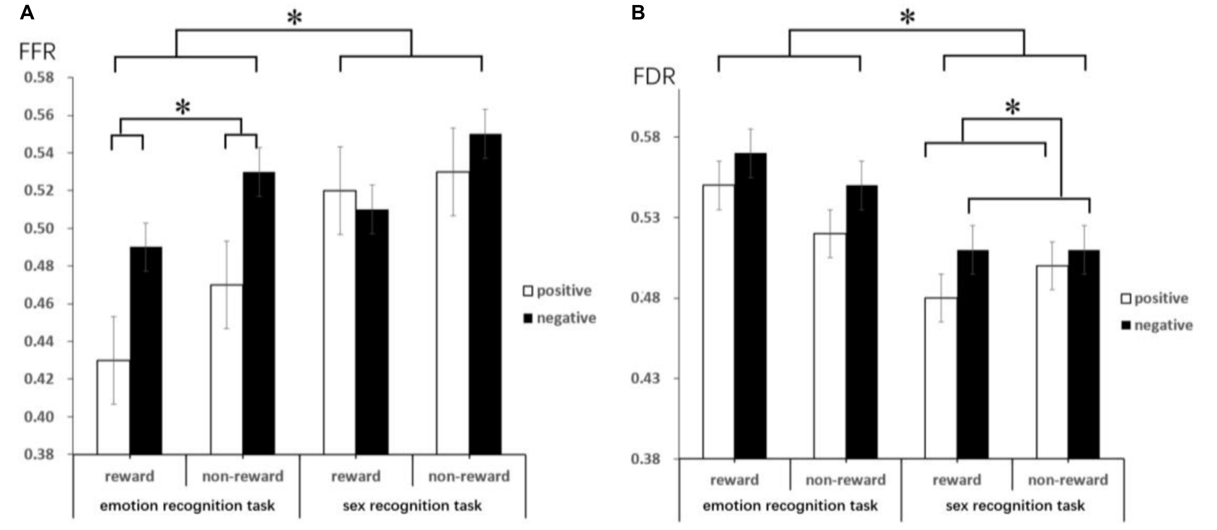

FIGURE 3 | This figure reveals the mean FFR **(A)** and FDR **(B)** by target, emotion type and reward anticipation. Error bars represent the standard error of the mean. These lines mainly indicate that there are significant differences under different conditions through the difference comparison test. *Represents $p < 0.05$.

the main effect of emotion was significant [$F(1,18) = 6.88$, $p = 0.02$, $\eta_p{}^2 = 0.28$; and $BF_{10} = 13.40$], with a lower FFR for positive faces than for negative faces, while the interaction between emotion and reward anticipation was not significant. In the sex recognition task, other main effects and interactions were not significant ($ps > 0.05$).

The ANOVA results indicate that the main effect of the target was marginally significant [$F(1,18) = 4.08$, $p = 0.059$, $\eta_p{}^2 = 0.19$; and $BF_{10} = 246.22$] on FDR, with a higher FDR in the emotion recognition task than in the sex recognition task. The main effect of emotion was also significant [$F(1,18) = 6.67$, $p < 0.05$, $\eta_p{}^2 = 0.27$; and $BF_{10} = 1.07$], with a lower FDR for positive faces than for negative faces. Other main effects and interactions were not significant ($ps > 0.05$). Separate repeated-measures ANOVA results show that in the sex recognition task, the main effect of emotion was significant [$F(1,18) = 4.41$, $p < 0.05$, $\eta_p{}^2 = 0.20$; and $BF_{10} = 4.07$], with a lower FDR for positive faces than for negative faces. Other main effects and interactions were not significant ($ps > 0.05$).

DISCUSSION

No interaction between reward anticipation and emotion was found in the emotion recognition or sex recognition tasks in this study. However, we found that the results in the two tasks were completely different. When the target was related to emotion (emotion recognition task), consistent with the research by Wei et al. (2014), the main effect of reward anticipation was significant. This may be because reward anticipation promotes the processing of the emotional attributes of a stimulus, so in the reward trials, the subjects showed shorter RTs and higher FFRs. While the target was unrelated to emotion (sex recognition task), consistent with the research by Kaltwasser et al. (2013), the main effect of reward anticipation was not significant. The subjects focused on the sex information of the stimulus, which interfered with the automatic processing of the emotional attributes of the stimulus. The processing of the emotional attributes of a stimulus is superior to the processing of other attributes to a certain extent, and it has a certain impact on the processing of other attributes (Yang et al., 2016); thus, reward anticipation promotes the processing of emotion and sex information at the same time. In a word, it suggests that the target itself regulates the effect that reward anticipation work on the processing target attribute. According to the theory of Murray (2007), reward anticipation cues influence behavior, whose underlying mechanism comprises two systems inside the amygdala running in parallel. One system can adjust the universal arousing effect of reward anticipation, while the other links the sensory properties of reward anticipation with emotion. Therefore, in the emotion recognition task, the two systems work together, resulting in shorter RTs and higher FFRs in reward trials. Meanwhile, the two systems of reward anticipation inside the amygdala run separately, resulting in the effect of reward anticipation being dispersed, which causes no significant main effect of reward anticipation. In other words, reward anticipation promotes emotion processing explicitly and automatically, but the processing of emotional information (such as the emotional attributes of stimuli) disperses part of the promotion effect of reward anticipation. The processing of emotion stimuli increases processing speed only when it is rewarded.

Consistent with previous studies (Hartikainen et al., 2014), this study indicated that subjects had a negative emotional bias during the face recognition process. Individuals exhibited a priority effect on unpleasant stimuli, especially threatening stimuli such as violence, bloody scenes and angry faces, which affected psychological processes and behavioral responses (Buckner et al., 2010). Similarly, the target influenced the effect of emotion on the response of the emotion process. According to the perceptual load theory, when attention resources are completely occupied by task-related content, the process of dealing with task-free interference will stop (Neumann et al., 2011), and emotional bias is affected by the perceptual load (Luo et al., 2017). Negative emotional bias appeared in the sex recognition task, indicating that some attention resources were allocated to emotional processing. However, in the emotion recognition task, compared with positive faces, subjects gazed at negative faces for a longer time but with lower processing quality. This was likely because more attentional resources were used to alert individuals to negative stimuli, and fewer cognitive resources were used for target-related processing, resulting in a higher RT (Zhu and Zhu, 2011; Ji, 2013) or lower accuracy. This indicates that the emotional valence of the stimulus might affect the overall attention processing quality. Individuals have a need to stay in a neutral state, and they may need to spend additional resources regulating the effect of negative emotion when processing stimuli. This reduces the processing speed and interference accuracy of the target-related process.

Although the target did not impact the interaction between reward anticipation and emotion, the results suggested that the main effect of the target was significant for FFR and FDR, which indicated that the target might affect the emotion attention process independently. Compared with the sex recognition task, the subjects had lower FFRs and higher FDRs in the emotion recognition task. This meant that the individuals tried to avoid emotional faces while holding a high level of attention maintenance when completing an emotion-related task. According to previous studies, if the target is valence related, the valence of faces will have additional effects on attention resource allocation (Schulz et al., 2013).

The rapid and effective identification and analysis of various types of information in complex environments are of great significance to the adaptation and development of individuals. The results of this study provide theoretical support for understanding individuals' emotion processing. This study found that reward anticipation promotes emotion processing explicitly and implicitly. We required the subjects to respond as quickly as possible during the practice trials (baseline). And in the formal trials, subjects can receive rewards only when their response was faster than the baseline, which required the subjects to pay close attention to the target. Besides, implicit processing of emotional faces included recognition of other facial cues, such as sex (Scheuerecker et al., 2007). In the emotion recognition task, in which emotion processing is explicit processing of faces, consistent with the research by Wei et al. (2014), the results show that reward anticipation promotes emotion processing; that is, reward anticipation promotes explicit emotion processing. In the sex recognition task, emotion processing is implicit processing of faces. The subjects showed higher processing quality in a shorter fixation duration for positive faces, while reward anticipation did not promote sex processing. It is inferred that this was due to the emotional content being automatically processed and interfered the effect of reward anticipation on sex processing (Rigoulot et al., 2012), and emotion processing was promoted, so we speculate reward anticipation promoted implicit emotion processing.

CONCLUSION

This study, which adopted a cue-target paradigm to explore the role of the target in the relationship between reward anticipation and emotion, drew the following conclusions: Target status can regulate the promotion of reward anticipation to emotional attention. Reward anticipation promotes explicit emotion processing. The emotional relevance of the target can impact the orientation and maintenance of attention to emotional faces. Emotional attributes may take processing priority over other attributes to a certain extent.

DATA AVAILABILITY STATEMENT

The database generated for this study is available upon request to the corresponding author.

ETHICS STATEMENT

This study was carried out in accordance with the recommendations of The ZJUT Human Research Ethics Committee. All subjects gave written informed consent in accordance with the Declaration of Helsinki. The protocol was approved by The ZJUT Human Research Ethics Committee.

AUTHOR CONTRIBUTIONS

YY and YX developed the study concept and design. Data collection was performed by RW. YY and YX performed the data analysis. All authors contributed to the data interpretation and manuscript writing and approved the final version of the manuscript for submission.

FUNDING

YY received support from National Education Science Planning Projects (ECA160410) and Preliminary Research Project in Humanities and Social Sciences of ZJUT.

REFERENCES

Anderson, B. A. (2013). A value-driven mechanism of attentional selection. *J. Vis.* 13, 1–16. doi: 10.1167/13.3.7

Armstrong, T., and Olatunji, B. O. (2012). Eye tracking of attention in affective disorders: a meta-analytic review and synthesis. *Clin. Psychol. Rev.* 32, 704–723. doi: 10.1016/j.cpr.2012.09.004

Aron, A., Fisher, H., Mashek, D. J., Strong, G., Li, H., and Brown, L. L. (2005). Reward, motivation, and emotion systems associated with early-stage intense romantic love. *J. Neurophysiol.* 94, 327–337. doi: 10.1152/jn.00838.2004

Berridge, K. C., and Robinson, T. E. (2003). Parsing reward. *Trends Neurosci.* 26, 507–513. doi: 10.1016/S0166-2236(03)00233-9

Buckner, J. D., Maner, J. K., and Schmidt, N. B. (2010). Difficulty disengaging attention from social threat in social anxiety. *Cogn. Ther. Res.* 34, 99–105. doi: 10.1007/s10608-008-9205-y

Carmona, S., Hoekzema, E., Ramosquiroga, J. A., Richarte, V., Canals, C., Bosch, R., et al. (2012). Response inhibition and reward anticipation in medication-naive adults with attention-deficit/hyperactivity disorder: a within-subject case-control neuroimaging study. *Hum. Brain Mapp.* 33, 2350–2361. doi: 10.1002/hbm.21368

Chen, J. (2013). *Study on the Characteristics of Nerve Activation in Patients With Depression*. Master's thesis, Qingdao University, Qingdao. .

Cisler, J. M., and Koster, E. H. (2010). Mechanisms of attentional biases towards threat in anxiety disorders: an integrative review. *Clin. Psychol. Rev.* 30, 203–216. doi: 10.1016/j.cpr.2009.11.003

Costa, V. D., Lang, P. J., Sabatinelli, D., Versace, F., and Bradley, M. M. (2010). Emotional imagery: assessing pleasure and arousal in the brain's reward circuitry. *Hum. Brain Mapp.* 31, 1446–1457. doi: 10.1002/hbm.20948

Deubel, H., O'Regan, J. K., and Radach, R. (2000). Attention, information processing and eye movement control. *Readi. Percept. Process* 4682, 355–374. doi: 10.1016/B978-008043642-5/50017-6

Engelmann, J. B., and Pessoa, L. (2007). Motivation sharpens exogenous spatial attention. *Emotion* 7, 668–674. doi: 10.1037/1528-3542.7.3.668

Fan, L., Qi, S., Guo, R., Huang, B., and Yang, D. (2014). Toward understanding the role of reward in attentional selection. *Adv. Psychol. Sci.* 22, 1573–1584.

Fox, E., Russo, R., Bowles, R., and Dutton, K. (2001). Do threatening stimuli draw or hold visual attention in subclinical anxiety? *J. Exp. Psychol. Gen.* 130, 681–700. doi: 10.1037//0096-3445.130.4.681

Hartikainen, K. M., Sun, L., Polvivaara, M., Brause, M., Lehtimäki, K., Haapasalo, J., et al. (2014). Immediate effects of deep brain stimulation of anterior thalamic nuclei on executive functions and emotion-attention interactions in humans. *J. Clin. Exp. Neuropsychol.* 36, 540–550. doi: 10.1080/13803395.2014.913554

Jeffreys, H. (1961). *Theory of Probability*, 3rd Edn. Oxford, UK: Oxford University Press.

Jerónimo, R., Volpert, H. I., and Bartholow, B. D. (2017). Event-related potentials reveal early attention bias for negative, unexpected behavior. *Soc. Neurosci.* 12, 232–236. doi: 10.1080/17470919.2016.1144646

Ji, W. (2013). *Facial Expression and Gaze-Direction in Face Perception*. Master's thesis, Suzhou University, Jiangsu.

Kaltwasser, L., Ries, S., Sommer, W., Knight, R. T., and Willems, R. M. (2013). Independence of valence and reward in emotional word processing: electrophysiological evidence. *Front. Psychol.* 4:168. doi: 10.3389/fpsyg.2013.00168

Liu, Y., and Reichle, E. D. (2018). Eye-movement evidence for object-based attention in chinese reading. *Psychol. Sci.* 29, 278–287. doi: 10.1177/0956797617734827

Luo, Y., Feng, L., Reng, M., Gu, Q., Zhao, S., and Zhang, Y. (2017). The effect of perceptual load on processing and memorizing negative facial distractor. *Acta Psychol. Sin.* 049, 1256–1266. doi: 10.3724/SP.J.1041.2017.01256

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2020.01170/full#supplementary-material

Murray, E. A. (2007). The amygdala, reward and emotion. *Trends Cogn. Sci.* 11, 489–497. doi: 10.1016/j.tics.2007.08.013

Näätänen, R. (1990). The role of attention in auditory information processing as revealed by event-related potentials and other brain measures of cognitive function. *Behav. Brain Sci.* 13, 201–288. doi: 10.1017/S0140525X00078407

Neumann, M. F., Mohamed, T. N., and Schweinberger, S. R. (2011). Face and object encoding under perceptual load: ERP evidence. *NeuroImage* 54, 3021–3027. doi: 10.1016/j.neuroimage.2010.10.075

Oldham, S., Murawski, C., Fornito, A., Youssef, G., Yücel, M., and Lorenzetti, V. (2018). The anticipation and outcome phases of reward and loss processing: a neuroimaging meta-analysis of the monetary incentive delay 0. *Hum. Brain Mapp.* 39, 3398–3418. doi: 10.1002/hbm.24184

Pessoa, L. (2009). How do emotion and motivation direct executive control? *Trends Cogn. Sci.* 13, 160–166. doi: 10.1016/j.tics.2009.01.006

Rigoulot, S., D'Hondt, F., Honoré, J., and Sequeira, H. (2012). Implicit emotional processing in peripheral vision: behavioral and neural evidence. *Neuropsychologia* 50, 2887–2896. doi: 10.1016/j.neuropsychologia.2012.08.015

Scheuerecker, J., Frodl, T., Koutsouleris, N., Zetzsche, T., Wiesmann, M., Kleemann, A. M., et al. (2007). Cerebral differences in explicit and implicit emotional processing–an fMRI study. *Neuropsychobiology* 56, 32–39. doi: 10.1159/000110726

Scholz, A., Klichowicz, A., and Krems, J. F. (2018). Covert shifts of attention can account for the functional role of "eye movements to nothing". *Mem. Cogn.* 46, 230–243. doi: 10.3758/s13421-017-0760-x

Schulz, C., Mothes-Lasch, M., and Straube, T. (2013). Automatic neural processing of disorder-related stimuli in social anxiety disorder: faces and more. *Front. Psychol.* 4:282. doi: 10.3389/fpsyg.2013.00282

Stavropoulos, K. K. M., and Carver, L. J. (2014). Reward anticipation and processing of social versus nonsocial stimuli in children with and without autism spectrum disorders. *J. Child Psychol. Psychiatry* 55, 1398–1408. doi: 10.1111/jcpp.12270

Trentacosta, C. J., and Fine, S. E. (2010). Emotion knowledge, social competence, and behavior problems in childhood and adolescence: a meta-analytic review. *Soc. Dev.* 19, 1–29. doi: 10.1111/j.1467-9507.2009.00543.x

Wang, Q., and Yu, G. (2017). The effect of stereotype threat on achievement motivation of teenagers with learning disability. *Psychol. Dev. Educ.* 33, 425–432. doi: 10.16187/j.cnki.issn1001-4918.2017.04.06

Wang, X. (2016). *The Role of Reward History and Working Memory in Guiding Visual Attention*. Master's thesis, Shandong Normal University, Shandong.

Wang, Y., and Luo, Y. (2005). Standardization and assessment of college students' facial expression of emotion. *Chin. J. Clin. Psychol.* 13, 396–398.

Wei, G. (2015). *Research on Undergraduate Students' Depression Impacts on the Brain Function of Reward System*. Master's thesis., Dalian Maritime, Dalian University.

Wei, P., and Kang, G. (2014). Task relevance regulates the interaction between reward expectation and emotion. *Exp. Brain Res.* 232:1783. doi: 10.1007/s00221-014-3870-8

Wei, P., Kang, G., Ding, J., and Guo, C. (2014). Monetary incentives modulate the processing of emotional facial expressions: an ERP study. *Acta Psychol. Sin.* 46, 437–449.

Wetzels, R., and Wagenmakers, E.-J. (2012). Default Bayesian hypothesis test for correlations and partial correlations. *Psychon. Bull. Rev.* 19, 1057–1064. doi: 10.3758/s13423-012-0295-x

Wittmann, B. C., Schiltz, K., Boehler, C. N., and Diizel, E. (2008). Mesolimbic interaction of emotional valence and reward improves memory formation. *Neuropsychologia* 46, 1000–1008. doi: 10.1016/j.neuropsychologia.2007.11.020

Wu, F., Gu, Q., Shi, Z., Gao, Z., and Shen, M. (2018). Striding over the "classical statistical inference trap"–Application of bayes factors in psychological studies. *Chin. J. Appl. Psychol.* 24, 195–202.

Yan, C., Su, L., Wang, Y., Xu, T., Yin, D. Z., Fan, M. X., et al. (2016). Multivariate neural representations of value during reward anticipation and consummation in the human orbitofrontal cortex. *Sci. Rep.* 6:29079. doi: 10.1038/srep29079

Yang, Q., Wang, X., Yin, S., Zhao, X., Tan, J., and Chen, A. (2016). Improved emotional conflict control triggered by the processing priority of negative emotion. *Scie. Rep.* 6:24302. doi: 10.1038/srep24302

Zhu, Y., and Zhu, Y. (2011). The influence of sceptibility to emotion on the speed of information processing. *J. Chongq. Normal Univ.* 28, 84–87. doi: 10.5603/IMH.2017.0009

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