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Multivariate pattern analysis of electroencephalography data reveals information predictive of charitable giving

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A R T I C L E I N F O

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A B S T R A C T

Charitable donations are an altruistic behavior whereby individuals donate money or other resources to benefit others while the recipient is normally absent from the context. Several psychological factors have been shown to influence charitable donations, including a cost-benefit analysis, the motivation to engage in altruistic behavior, and the perceived psychological benefits of donation. Recent work has identified the ventral medial prefrontal cortex (MPFC) for assigning value to options in social decision making tasks, with other regions involved in empathy and emotion contributing input to the value computation (*e.g.* Hare et al., 2010; Hutcherson et al., 2015; Tusche et al., 2016). Most impressively, multivariate pattern analysis (MVPA) has been applied to fMRI data to predict donation behavior on a trial-by-trial basis from ventral MPFC activity (Hare et al., 2010) while identifying the contribution of emotional processing in other regions to the value computation (*e.g.* Tusche et al., 2016). MVPA of EEG data may be able to provide further insight into the timing and scalp topography of neural activity related to both value computation and emotional effects on donation behavior. We examined the effect of incidental emotional states and the perceived urgency of the charitable cause on donation behavior using support vector regression on EEG data to predict donation amount on a trial by trial basis. We used positive, negative, and neutral pictures to induce incidental emotional states in participants before they made donation decisions concerning two types of charities. One category of charity was oriented toward saving people from current suffering, and the other was to prevent future suffering. Behaviorally, subjects donated more money in a negative emotional state relative to other emotional states, and more money to alleviate current over future suffering. The data-driven multivariate pattern analysis revealed that the electrophysiological activity elicited by both emotion-priming pictures and charity cues could predict the variation in donation magnitude on a trial-by-trial basis.

1. Introduction

Human beings are thought to be inherently selfish, aiming to maximize their interests from the perspective of classical economic theory (Camerer and Fehr, 2006; Dawkins, 2016). However, numerous studies have shown that people commonly behave prosocially (Henrich et al., 2005), for example, sacrificing their own interests to protect others from electric shocks (Crockett et al., 2015). As a kind of costly altruistic behavior, charitable donations normally require the decision-maker to trade-off personal costs in favor of others' interests (Qu et al., 2019; Rilling and Sanfey, 2011). The motivation behind charitable donation has been the subject of a wealth of social science research (for a review see Bekkers and Wiepking 2011), but only recently have neuroimaging techniques been applied to associating philanthropic behavior with neural activity (*e.g.* Moll et al., 2006; Tankersley et al., 2007; Harbaugh et al., 2007; Hare et al., 2010; Morishima et al., 2012; Kuss et al., 2013; Sawe and Knutson, 2015; Zaki et al., 2014; Hutcherson et al., 2015; Carlson et al., 2016; Tusche et al., 2016; Spaan et al., 2019; for a recent meta-analysis of fMRI studies on altruism see Cutler and Campbell-Meiklejohn, 2019).

Of primary interest is the question of what factors affect philanthropic behavior. Bekkers and Wiepking (2011) review over 500 articles on philanthropy and identify eight determinants of charitable giving: (1) awareness of need; (2) solicitation; (3) costs and benefits; (4) altruism; (5) reputation; (6) psychological benefits; (7) values; and (8) efficacy. Of these eight determinants, cognitive neuroscience research has focused on the neural underpinnings associated with altruistic motivation, as-

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sociated with the psychological benefits of giving, and associated with cost/benefit analysis.

Individual differences in altruism is linked to gray matter volume in the right temporoparietal junction (RTPJ), whereby more gray matter is predictive of more altruistic behavior (Morishima et al., 2012). RTPJ activity correlates with value ascribed to a choice benefiting others Hutcherson et al. (2015), and RTPJ activity as well as anterior insula activity is predictive of whether participants choose to make high vs low donations on a trial by trial basis (Tusche et al., 2016). Tusche and colleagues (2016) further dissociated the role of RTPJ and anterior insula in donation behavior with support vector regression (SVR) analysis of BOLD data, revealing that RTPJ coded cognitive perspective taking, whereas anterior insula coded affective empathy. This work and more suggest the RTPJ plays a primary role in the ability to take another person's perspective (see also Saxe and Powell, 2006; Decety and Jackson, 2006), and also highlights the key role of emotional responses in driving donation behavior.

Whereas the RTPJ appears to perform computations related to the value of a choice for others, the ventral striatum exhibits activity that correlates with value assigned to choices benefiting the self (Moll et al., 2006; Harbaugh et al., 2007; Hutcherson et al., 2015; see also Sawe and Knutson, 2015), and the ventral medial prefrontal cortex (ventral MPFC) integrates all this information into a single value signal (Hare et al., 2010; Hutcherson et al., 2015, Tusche et al., 2016). In all these studies, the BOLD signal predicts donation behavior on a trial-by-trial level, albeit at a course resolution, such as distinguishing between donating or not donating (Sawe and Knutson, 2015), or between the highest 50% of donations and the lowest 50% (*e.g.* Tusche et al. 2016). An exception is Hare and colleagues (2010) who showed that activity in ventral MPFC correlated with donation amount across trials, within-subjects. This important work also linked charitable donation behavior to other experiments showing value encoding in the ventral MPFC, and highlighted the broad range value computations-from primary to secondary, from concrete to abstract-that engage the ventral MPFC (Hare et al., 2008, 2010; Hare et al., 2009; see also Scholz et al., 2017; Genevsky et al., 2017; Dore et al., 2019).

Although not widely utilized in charitable donation studies, event-related potentials (ERPs) provide useful information about the timing of neural processes involved in social decisions (Amodio et al., 2014). Multivariate pattern analysis (MVPA) of ERP data offers a powerful method for extracting information at trial-by-trial resolution, and has recently and successfully been utilized in EEG studies (Stokes et al., 2015; Grootswagers et al., 2017; Bae and Luck, 2018, 2019; Bode et al., 2019). ERPs are typically sensitive to activity in the MPFC, as found in localization studies (e.g. Holroyd and Coles 2002, Miltner et al., 1997; Nieuwenhuis et al., 2003) and joint ERP fMRI studies (Hauser et al., 2014; Iannaccone, et al., 2015). Thus, this work was directed at replicating and extending the findings from Hare et al. (2010) and Tusche et al. (2016) using SVR to predict donation amount trial-by-trial on the basis of MPFC activity, while simultaneously getting a clear picture of the timing of the donation-predictive neural activity. We first used the spatiotemporal decoding to test whether particular spatiotemporal features in the single-trial ERPs could predict a participant's trial-by-trial donation amount. Following this, we subjected the data to conventional ERP analysis to link our MVPA findings to established ERP components and to examine the sequential stages of emotion-related decisions at the average waveform level (Schupp et al., 2006).

A second purpose of this work is to determine how emotional states impact donation decisions. Previous studies have found that incidental emotional states influence subsequent prosocial behaviors (Clark and Waddell, 1983; Shaffer and Graziano, 1983; Gendolla, 2000). Human altruism can be facilitated by positive emotions, for example, when emotions were primed by the participant's favorite music (Fukui and Toyoshima, 2014) or by positive words such as 'love' (Lamy et al., 2012). Negative emotions such as stress can also provoke prosocial behaviors (von Dawans et al., 2012). For example, negative mood increases giving in the dictator game (Tan and Forgas, 2010; Pérez-Dueñas et al. 2018). However, the role of incidental emotion in affecting donation behavior specifically has never been studied. This work investigated the behavioral effects of emotion primed by affective images, and the neural activity associated with these effects. Furthermore, there are multiple ERP components that are sensitive to the emotional content of images, ranging from early visual components such as the P1 (*e.g.* Carretié et al., 2004) to the early posterior negativity (EPN) and the late positive potential (LPP) (Schupp et al., 2006; Olofsson et al., 2008; Liu et al., 2012). Both the EPN and the LPP typically index the emotional engagement of subjects (Sabatinelli et al., 2013). We thus hypothesized that EEG activity related to the task-irrelevant emotional reaction to the priming images would also be predictive of donation behavior.

One final question to be addressed in this work is the effect of perceived need on donation behavior. Bekkers and Wiepking (2011) specified awareness of need as a crucial factor impacting donation decisions. Few people donate blood on a regular basis to prepare for future public emergencies, but many donate when there is a current emergency (Godin, et al., 2005; Olaiya et al., 2004). This exact phenomenon has not been studied experimentally, however it is assumed that both awareness of need (seeing news stories about the emergency) and perceived urgency (having the urgency described in those news stories) contribute to increased donation behavior. Further understanding of why people tend to be reactive rather than proactive in their donation behavior could have implications for preparing for emergencies. However, the effect of perceived urgency on donation behavior has only been tested experimentally, and speculated on regarding environmental issues (Sen, 1995; Sawe and Knutson, 2015).

Dickert and colleagues (2011) proposed the two-stage model of the role of emotions in donation behavior: Emotions focused on one's self determine the probability of making a donation, whereas emotions focused on others determine the magnitude of the donation. In the current work, we can examine the role of both emotions focused on the self (task-irrelevant emotion) and emotion focused on the charity (feeling of urgency). One possible interaction of these two variables is that the negative emotion associated with a feeling of urgency may counteract the positive priming of emotions. This would suggest it is the overall intensity of an individual's emotional state that drives donation behavior, rather than specific positive or negative valence or direction of focus. Alternatively, specific effects of emotional priming and charity type without an interaction would suggest independent effects of charitable donations.

2. Methods

2.1. Participants

Twenty-five participants (age range = 18–24; *M* age = 20.24; *SD* = 1.42; 12 females) were recruited from Shenzhen University. All participants were right-handed, had normal or corrected-to-normal vision, and had no history of psychiatric diagnoses, neurological or metabolic illnesses. Participants were compensated ¥50 for completing the study and had a chance to receive additional ¥1–9, depending on how much of that portion the participants chose to donate. The study was approved by the Shenzhen University ethics committee(20160303). Participants gave written informed consent prior to the experiment. The sample size was determined using a priori power analysis in G*Power 3 (Faul et al., 2007), specifying a medium effect size because no previous ERP studies on the effect of incidental emotions on donation behavior were available as reference effect sizes. In repeated measures analysis of variance (ANOVA), a medium effect size $f = 0.25$, power $(1-\beta) = 0.8$, and $\alpha = 0.05$, would require a total sample size of at least 19 participants. Note that the present power analysis was directed at estimating sample size for random effects in conventional ERP analysis, not for the fixed-effect in the MVPA analysis (Allefeld et al., 2016). We recruited six additional participants in anticipation of having to exclude some subjects for data loss due to recording noise, or especially poor task performance. Fortunately, no participants had to be excluded.

2.2. Procedure

2.2.1. The pilot experiment

Pre-experiment rating of priming pictures. First, we selected 60 pictures that elicit sad/happy/neutral emotions from the Chinese Affective Picture System (CAPS, Lu et al., 2005) and the International Affective Picture System (IAPS, Lang et al., 2008). All emotion pictures were 433 × 315 pixels with the horizontal and vertical visual angles below 6.5 $^{\circ}$. There were no significant differences in mean luminance between positive pictures (124.18 ± 43.42), negative pictures (124.94 ± 45.28) and neutral pictures (126.92 ± 35.94) (*ps* > 0.78); there were no differences in contrast between conditions: positive images (252 ± 7.8), negative images (251 ± 8.4) and neutral images (252 ± 9.2, *ps* > 0.43); nor were there any significant differences in spatial frequency between conditions: positive images (0.48 ± 0.27), negative images (0.48 ± 0.18) and neutral images (0.45 ± 0.26, *ps* > 0.63). These analyze suggested the low-level visual characteristics of the images were comparable between all conditions.

Thirty participants (18 females) from Shenzhen University were recruited to rate pictures for affective valence (happy versus sad) and arousal on a 9-point scale. The 30 pictures of garnering the highest affective intensity ratings (> 5) were selected for each emotion category with intensity matched between positive and negative emotion pictures, as described in the next paragraph.

The emotional intensity of the final three categories of emotional pictures was measured to check that the negative and positive pictures aroused comparable emotional intensity relative to neutral pictures. On a 9-point Likert scale, 5 is neutral, thus scores above 5 are positive and scores below 5 are negative. We took the absolute difference of mean positive-category scores from 5 and compared to the absolute difference of mean negative-category scores from 5 and submitted the results to a paired t-test. As such, the negative- ($M \pm SD$, 2.83 ± 0.54) and positive- (7.11 ± 0.25) category intensity scores were not significantly different from each other (t (29) = -0.593, p = 0.557). Moreover, the same procedure on the original arousal scores from the picture sets also showed the subset of positive (5.72 ± 0.54) and negative (5.61 ± 0.48) pictures used in this study did not differ significantly on emotional intensity (t (29) = 1.296, p = 0.205).

Selecting donation project material. Ten charity projects were selected from the Alipay Philanthropy website, with the condition that the charity description could be altered minimally to focus on current or future need. For example, The Health Action on School charity project contributes to a fund to provide free medical assistance to students with illnesses in poor areas (saving from current suffering). A complimentary version of the description was created, that focuses on preventing future suffering, describing a fund to set up school health clinics for poor schools and spread health knowledge to prevent disease. This procedure resulted in 20 charity descriptions in total. Pilot participants provided ratings on a five-point Likert scale oriented to assessing the subjective importance of each of these 20 charities. Ratings of importance were compared between the saving and prevention conditions, and the five charities from each condition with the smallest difference in importance scores were selected for the experiment (see APPENDIX I). The mean importance rating for the saving focus was 4.53 ± 0.42, range 3–5, and for the prevention focus was (4.43 ± 0.36, range 4,5). These values did not differ significantly, t (29) = -1.702, p = 0.1.

2.2.2. The formal experiment

Questionnaires. Participants were required to complete questionnaires directed at measuring empathy and prosocial tendencies before the ERP experiment. The Interpersonal Reactivity Index (IRI) (Davis, 1983) takes into account both affective and cognitive aspects of empathy and is one of the most commonly used, comprehensive self-report instruments designed to assess empathetic tendencies. The test-retest reliability of the subscales ranges from 0.59 to 0.78 (Rong et al., 2010). The Prosocial Tendencies Measure (PTM) (Carlo and Randall, 2002) is a widely used self-report inventory assessing prosocial tendencies. It contains 23 items and measures prosocial tendencies on six dimensions: altruistic, compliant, emotional, dire, public, and anonymous using a five-point Likert scale (Kou et al., 2007). Finally, the Positive and Negative Affect Scale (PANAS) (Watson et al., 1988; Huang et al., 2003) questionnaire was used on a block-by-block basis to assess the participant's ongoing emotional state. The PANAS has two dimensions: positive and negative, with 10 items in each dimension to be rated on a five-point Likert scale.

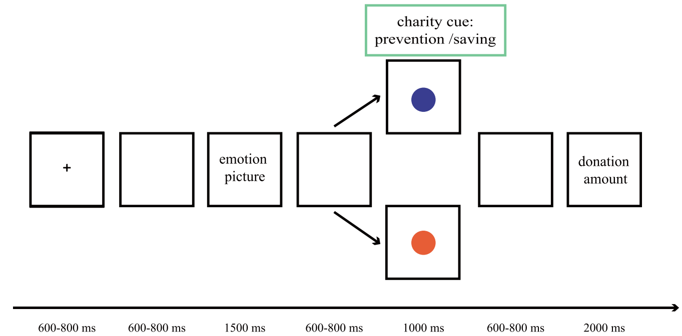

Fig. 1. Time course of stimulus presentation in the task.

The charitable donation task. The ERP experiment lasted nearly an hour and was divided into three emotion priming blocks with the order counterbalanced across participants. Participants were given breaks between blocks (see below). At the beginning and end of each block, participants responded to the PANAS questionnaire to assess their emotional state. At the end of each section, participants were required to rest for 7,8 min to ensure that the participants' emotional state was approximately the same before each priming session began. Before the ERP task, participants were required to read about the example charity projects. The participants were told that the charities were divided into two categories, defined by whether they targeted victims currently suffering ('saving') or potential victims in the future ('preventing'), and that these two categories would be cued by purple and orange circles during the task. The color mapping was counter balanced between the subjects.

The task was presented using E-prime 2.0 (PST). Fig. 1 illustrates the timing and events of each trial. First, a black fixation '+' was presented in the center of the screen for 600–800 ms (jittered) followed by a blank interval of 600–800 ms (jittered). Afterward, an emotional prime picture was presented for 1500 ms, and participants were instructed to try to feel the emotion evoked by the pictures. Next was another blank jittered interval of 600–800 ms, and then the charity cue was presented for 1000 ms. The charity cue was a purple or orange circle that indicated the donation target on the current trial (saving or preventing). The matches between the color of the circle and the particular donation target were counterbalanced across participants. After another jittered blank interval (600–800 ms), participants saw the donation request screen, during which participants had to make a donation amount choice by pressing the numeric keys of the keyboard. The donation amount possible was restricted to between ¥1 and ¥9, corresponding to the number keys 1 to 9.

Participants were informed that one trial from the experiment would be randomly selected to make corresponding, real donation to the charity in question after the ERP experiment (*e.g.* Hare et al., 2010). That is, participants donated with the understanding that one of their donation decisions would be truly implemented. This was mild deception in that for each pair of prevention and saving charities, there was only one true, associated charity (not both a prevention and saving version). The one true associated charity received the donation. Participants were debriefed about this mild deception after the experiment was complete. Participants received an initial endowment of ¥10 per round for a donation. As a reward for taking part in the experiment, participants were paid a fixed amount of ¥50 plus extra money (¥1–9).

2.3. EEG recording and preprocessing

Continuous EEG data were recorded using 64 Ag-AgCl unipolar leads on a 64-lead skullcap arranged according to the extended 10–20 system (Brain Products ActiCap). Data were bandpass filtered during recording at 0.016–100 Hz and digitized at 1000 Hz. Electrode FCz was used as a reference online, and the ground electrode was placed between FPz and Fz. The vertical electrooculogram (VEOG) was obtained via a facial electrode located 1 cm below the center of the right eye. The impedance for all electrodes was kept below 10 kΩ.

EEG data were preprocessed offline using EEGLAB version 12.8 software package (Delorme and Makeig, 2004) based on the MATLAB version R2018a (MathWorks). The EEG data was first downsampled to 500 Hz and re-referenced to the average of EEG activity recorded from electrodes at the left and right mastoids. A 0.1–30 Hz bandpass filter was applied to EEG data offline. Eyeblink and ocular artifacts were corrected using independent component analysis (Lee et al., 1999). The EEG data was epoched from -200 ms to 1000 ms relative to stimulus onset for all conditions, time-locked to the priming pictures in the priming phase and the charity cue in the charity cue phase. Each epoch was baseline corrected by subtracting the average baseline activity (-200 ms to 0 ms) at each channel from the entire epoch. Epochs with absolute amplitude values greater than 70 μV were identified as artifacts and excluded from analysis separately for each channel. This resulted in an average of 0.44 % of trials being eliminated per subject. Finally, the EEG data were averaged within each condition, locked to both the priming pictures and the cue stimuli.

2.4. Data analyze

2.4.1. Behavioral data analyze

The present study adopted a 3 (affective priming type: positive, neutral or negative) × 2 (donation target: prevention or saving) design. SPSS version 21 software was used for subsequent data analyze. To examine participants' emotional state changes in positive, neutral and negative priming blocks, the pretest-posttest PANAS scores were submitted to a three-way repeated measures ANOVA with emotion priming (positive, neutral, negative), emotion dimension self-report score (positive or negative) and testing phase (pre, post) as within-subjects variables. In addition, a 3 (emotion priming type: positive, neutral or negative) × 2 (donation target: prevention or saving) repeated measures ANOVA was performed to examine the amount of donated money.

2.4.2. MVPA analyze

The aim of MVPA analysis was to explore whether participant's donation at the single trial level could be predicted by features of the EEG elicited by the emotion-priming picture and charity cue. To do so, the preprocessed epoch from -200 ms to 1000 ms in each single trial were first downsampled to 250 Hz and then divided into 60 non-overlapping, small time windows of 20 ms each (Quek and Rossion, 2017; Turner et al., 2017), for all of the channels. The 20 ms time window was used to enhance single-to-noise ratio, as in previous studies (Bode et al., 2014; Schubert et al., 2020). These data, including all six experiment conditions for each participant, were submitted to a support vector regression (SVR) classifier using LIBSVM with a standard cost parameter C = 0.1 (Chang and Lin, 2011). The MVPA was carried out by the Decision Decoding Toolbox (Version1.0.4; DDTBOX; Bode et al., 2019). The classifier was trained in decoding features from 80% randomly selected trials to predict donation magnitude on those trials, and then tested on the remaining 20% of trials (*e.g.* Quek and Rossion, 2017; Turner et al., 2017). To avoid selection biases, the entire analysis was repeated five times with random division between training and test data (Sassenhagen and Fiebach, 2019). The performance of SVR was assessed by correlating the predicted money amount for each data point in the test data with the actual donated money. The decoding accuracy was calculated as the average accuracy after five-fold cross-validation (Sassenhagen and Fiebach, 2019) and assigned to the onset of the respective time window. Finally, these correlation coefficients were Fisher Z-transformed for further statistical analyze.

The SVR analysis was also conducted on randomly shuffled labels for each participant and each analysis time window in order to obtain a distribution of accuracies by permutation. For group level statistical analyze, t-tests using a threshold of $p < 0.05$ were used to compare the empirical results with permutation test results (Bode et al., 2012; Bode et al., 2014). Subsequently, cluster-based permutation testing (number of iterations = 10000, alpha level of 0.05) was conducted for multiple comparisons correction.

We also ran the SVR analysis on each emotion condition in the priming phase and donation-target phase separately, in order to exert maximally rigorous control over any unintended, between-condition differences that could possibly be driving the SVR success. That is, because the emotional priming affected donation amount, the SVR could potentially leverage brain responses to irrelevant differences between conditions to achieve success, such as time-on-task effects due to the between-block emotional priming manipulation. Note that low-level perceptual features of the priming images such as luminance, contrast, and spatial frequency did not differ significantly between conditions, but that does not rule out that they could be contributing. In this second analysis the SVR was run on far fewer trials than the across-condition analysis, and should be expected to lose some sensitivity. In an effort to preserve as much sensitivity as possible, the SVR was run on each condition separately, but then the resulting Fisher-transformed correlation coefficients were averaged across the three emotion conditions.

For the feature weight analysis, the absolute feature weights were extracted for each time point and channel within each significant cluster, and each channel weight for that clusters was calculated as the average feature weight across the cluster time window at that channel. Raw feature weights were transformed using the method introduced by Haufe et al. (2014) to ensure accurate topographies. For further statistical analysis, the transformed feature weights were further z-scored and corrected by FDR (Benjamini and Hochberg, 1995) for controlling multiple comparison.

2.4.3. EEG data analyze

According to previous studies (Schupp et al., 2006; Olofsson et al., 2008; Liu et al., 2012), we focused on the EPN and LPP components time-locked to the emotion-priming picture. To compare the EEG activity in emotional image processing, the EPN was measured as the mean amplitude in the 230–300 ms time window following image onset at FCz, and the mean amplitude of LPP was computed in the 600–900 ms time window at CPz (Weinberg and Sandre, 2018). The EPN and LPP were submitted to one-way repeated measures ANOVAs to examine emotional image processing.

In the charity cue phase, following up on the MVPA analysis, we focused on the negativity at electrode FCz between 260–350 ms that was predictive of donation behavior at the single-trial level. The mean amplitude of this negativity was submitted to a 3 (emotion priming: positive, neutral or negative) × 2 (donation target: prevention or saving) repeated measures ANOVA for the donation target phase. The Greenhouse-Geisser correction was applied where necessary.

2.4.4. Correlation between ERP amplitude and behavioral analyze

Additionally, to compare with the MVPA results, we also calculated the correlation between donation amount and single trial ERP amplitude. First, we downsampled the single-trial ERP to 250 Hz and calculated the Pearson correlation between donation amount and mean ERP

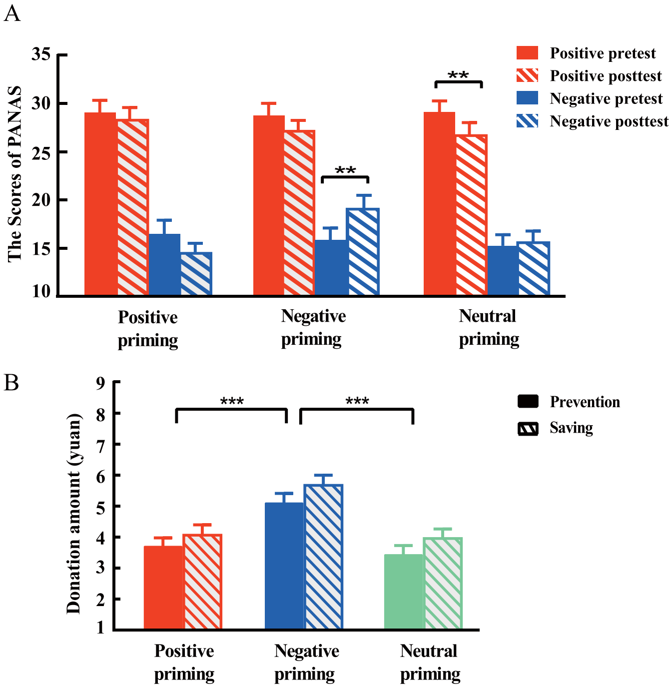

Fig. 2. (A)Pretest and posttest scores of PANAS. The red bars represent emotion rating in the positive dimension and the blue bars represent emotion rating in the negative dimension on the PANAS scale. The solid bars represent pretest ratings while the diagonal bars represent posttest ratings. Error bars stand for SE here and hereafter. ** $p < 0.01$, *** $p < 0.001$. (B) Donation amount. The red, blue and green colors represent positive, negative and neutral priming respectively. The solid and diagonal bars represent the Prevention (future need) and Saving (current need) categories of charities, respectively (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

amplitude at each 20 ms time-window (five time-points) at each electrode. The 20 ms time-window was used to match with MVPA. These r values were transformed to fisher Z values. Given that the MVPA used all features of all electrodes to train the temporal pattern, we also averaged Z values from all electrodes for each time window in this conventional correlation analysis. A cluster-based permutation with 10000 iterations was used to correct for multiple comparisons. These procedures were carried out for both the ERPs elicited by priming pictures by charity cues separately. No significant results were found. The results of these conventional correlations were reported in the Appendix (see Fig. S3).

3. Results

3.1. Behavioral results

Emotion priming effect. Pretest and posttest scores for the PANAS are shown in Fig. 2A. A testing phase × emotion priming type × emotion dimension interaction effect reached significance, F (2,48) = 3.707, p = 0.043, $\eta 2$ p = 0.134. Simple effects analysis revealed that the posttest scores for the negative dimension in the negative emotion priming ($M \pm SE$, 18.80 ± 1.49) were significantly higher than pretest scores (15.52 ± 1.24, $p = 0.003$) and also differed from positive (14.04 ± 1.00, $p = 0.002$) and neutral emotion priming (15.32 ± 1.22, $p = 0.002$). The pretest-posttest score differences in the positive dimensions initiated by neutral emotion also reached significance (p = 0.003) (Fig. 2A). Additionally, the positive priming revealed a marginally significant trend in reducing negative emotion ($p = 0.087$). These results indicate that participants were effectively primed to feel negative emotions in the negative priming condition, but the priming effect in the positive priming condition did not reach statistical significance.

Donation amount. Donation amounts for each condition are shown in Fig. 2B and Fig.S1. A two-way repeated measures ANOVA for donation amount revealed a significant main effect of emotion priming, F (2,48) = 30.847, p < 0.001, $\eta 2$ p = 0.562. Pairwise comparisons showed that the donated money in the negative emotion priming condition ($M \pm SE$, 5.39 ± 0.33) was significantly different from positive (3.83 ± 0.33) and neutral emotion priming (3.67 ± 0.31, all p < 0.001). There was also a significant main effect of donation target, F (1,24) = 17.008, p < 0.001, $\eta 2$ p = 0.415, with less money donated to prevention (future need) charities (4.04 ± 0.30) than saving (current need) charities (4.56 ± 0.30). However, there was no significant interaction effect between emotion priming and donation target, F (2,48) = 0.557, p = 0.576, $\eta 2$ p = 0.023.

3.2. ERP results

3.2.1. Emotion priming image phase: MVPA results

The spatiotemporal decoding of single-trial ERPs showed that several time-windows in the emotion priming phase were significantly correlated with donation amount ($p < 0.05$, corrected by cluster-based permutation test, Fig. 3). Based on the scalp distribution of feature weights, we divided the four clusters into three phases (early: 160–400 ms, intermediate: 480–560 ms & late: 800–920 ms). Feature weights analysis showed that the frontal-central and central-posterior regions were the main contributors to SVR accuracy, with both combining in in the latest time window, the central-posterior being the primary contributor in the second window, and the frontal-central region being the primary contributor in the first window. These results suggest that the single-trial ERPs elicited by emotional images could predict subsequent donation amount as early as 160 ms. Note that a complimentary analysis was run on the data with occipital channels excluded to minimize the chance that low-level visual differences between conditions was driving SVR accuracy. This analysis yielded largely the same results (see Appendix, Fig. S4).

The SVR was also run on each priming condition separately as a stringent control on potential unintended differences between priming conditions. When run in this manner, the SVR failed to find significant clusters in the early and intermediate time windows, but it did find a cluster at frontal-central electrodes significantly predictive of donation amount that overlapped with the above results in the late time window (880–1000 ms, Fig. 4). Thus, this frontal-central, late time-window cluster was significant both when the more sensitive, across-conditions SVR was run, and when the less sensitive but more highly controlled second SVR was run. It is impossible to know if the early and intermediate clusters were not found in the more controlled analysis because of the removal of the influence of potential confounds, or because of the loss of sensitivity due to fewer trials in each analysis. Note that to determine if the late cluster extended beyond 1000 ms we ran another analysis on epochs extending out to 1500 ms, which revealed largely the same cluster, and with the significance window ending at approximately 1000 ms (see Appendix, Fig. S6).

3.2.2. Emotion priming image phase: ERP results

The ANOVA for the mean amplitude of the EPN[1] at 230 to 300 ms revealed an emotion priming type effect, F (2,48) = 8.636, $p < 0.001$, $\eta 2$ p= 0.265. Pairwise comparison showed that the amplitude of positive ($M \pm SE$, -9.08 ± 0.69, $p = 0.003$) and negative (-9.07 ± 0.74, $p = 0.001$) emotion priming was greater than neutral's (-7.70 ± 0.67), although

[1] Given that researchers in the emotion priming field commonly use an average reference to analyze the EPN associated with emotional pictures, we analyzed the data twice, once with linked mastoids as reference, and once with the average reference. The results with average reference showed the same pattern exhibited here (using the linked mastoids) (Junghöfer et al., 2006; Eimer and Holmes, 2007; Rellecke et al., 2013).

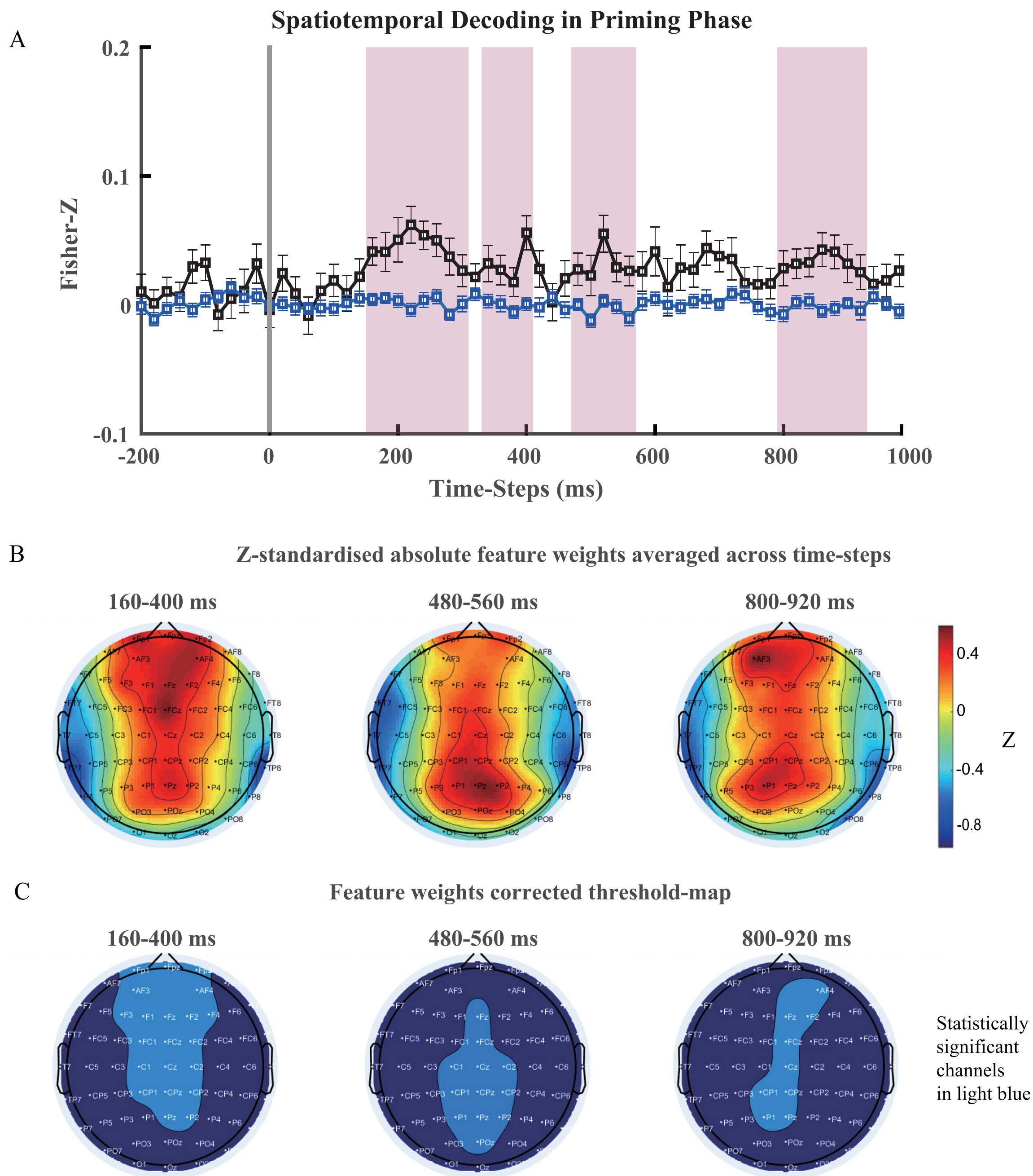

Fig. 3. Emotion priming image phase. (A) Spatiotemporal decoding accuracy across all channels. *Y*-axis represents the Fisher-*Z* score of training data and testing data and *X*-axis shows the time course (step size = 20 ms, window width = 20 ms). The black and blue lines show the actual accuracy and permutation test results respectively. Error bars indicate standard error of the mean. The pink bars indicate the decoding accuracy was significant across these time steps ($p < 0.05$, corrected for multiple comparison). (B) *Z*-standardized absolute feature weights on different channels across three time windows and (C) Feature weights after corrected for multiple comparison, light blue locations are significant channels (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

positive and negative emotion priming was not significantly different ($p = 0.982$) (Fig. 5).

LPP mean amplitude between 600 and 900 ms also exhibited a significant main effect of emotion priming, F (2,48) = 15.092, $p < 0.001$, $\eta 2$ p= 0.386, with greater amplitude elicited by positive ($M \pm SE$, 2.43 ± 0.66) and negative emotion priming (3.08 ± 0.70) than neutral emotion priming (0.61 ± 0.60, all $p < 0.001$) As with the EPN, positive and negative emotion priming were not significantly different ($p = 0.232$) (Fig. 6). These ERP results indicated that emotional pictures elicited larger EPN and LPP amplitude than neutral pictures, suggesting that the emotion priming manipulation was effective at the neural level.

3.2.3. Donation target phase: MVPA results

As shown in Fig. 7, the spatiotemporal decoding results revealed that the time window from 180 to 440 ms (except 280 ms) was predictive of participants' real donation amount in single trials ($p < 0.05$, corrected by cluster-based permutation test). Moreover, the spatial decoding in this time window (180–440 ms) produced feature weights generated from the frontal-central region of the scalp. A duplicate analysis with occipital

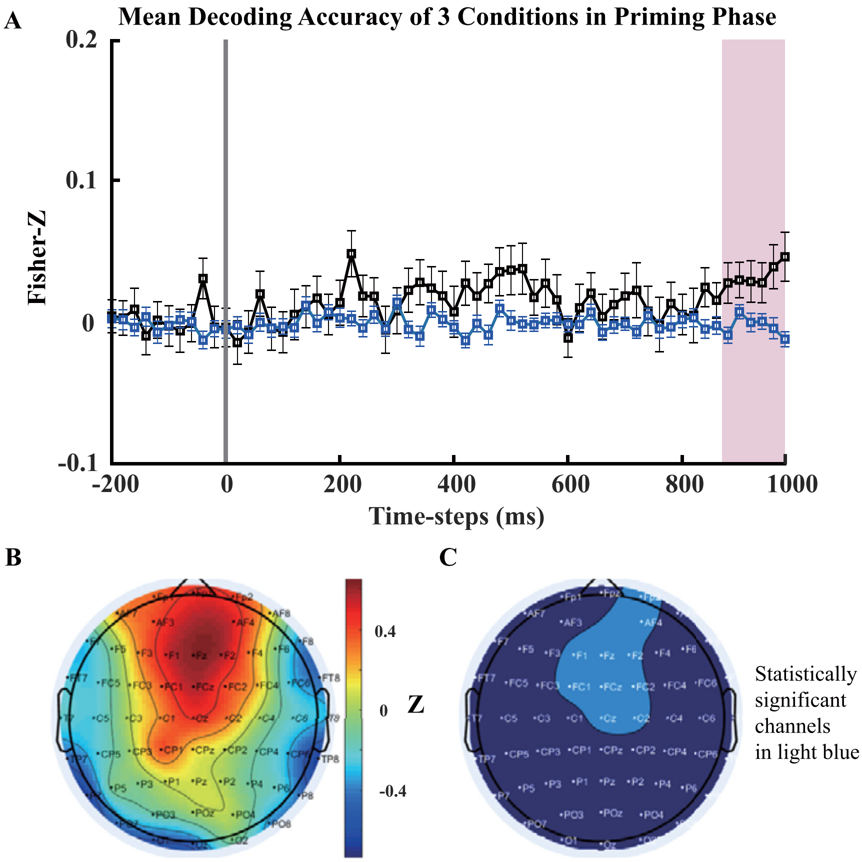

Fig. 4. (A) The mean decoding performance (Fisher-transformed correlation coefficients) across the three emotion conditions in the priming image phase. The pink area indicates the decoding performance on real data was significantly larger than that on randomly permuted data in this cluster after multiple comparison correction. Note that the Fisher-*Z* score in this cluster was also significantly larger than zero. (B) *Z*-standardized absolute feature weights on different channels across time steps (880–1000 ms). (C)Feature weights after correction for multiple comparisons (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

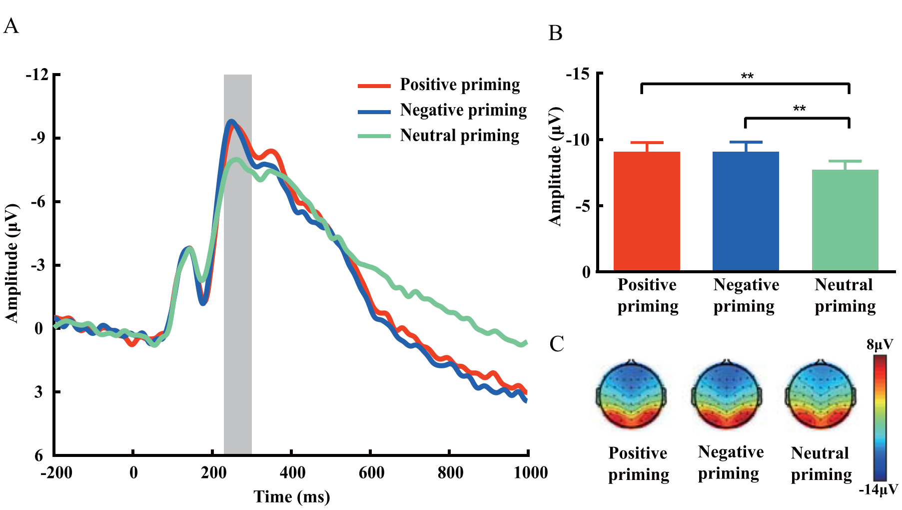

Fig. 5. (A) The EPN waves for the emotional picture presentation at FCz. Gray shaded area shows the 230-300 ms analysis window in which the EPN was quantified. (B) Mean values of EPN amplitude in each condition. ** $p < 0.01$. (C) Topographic maps for positive / negative / neutral emotion priming (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

electrodes excluded yielded almost identical results (see Appendix, Fig. S5).

As with the priming phase, we ran the SVR in each emotion condition separately. This method of analysis failed to reveal the significant frontal-central cluster observed between 180 and 440 ms, but instead showed an effect between 900 and 1000 ms (Fig. 8A). Running the same analysis on epochs extending out to 1500 ms suggested the cluster was confined to largely the 900 to1000 ms time window. The feature weights analysis showed that the frontal-central region contributed to the significant cluster that could predict donation amount (Fig. 8B). It is important to note again that each SVR was run on only one third of the trials that went into the across-condition analysis, and would thus be less sensitive to informative clusters. Thus, the SVR results from the donation-target phase should be treated with caution, but not discounted.

3.2.4. *Donation target phase: ERP results*

The MVPA results indicated that electrophysiological activity between 180–440 ms at frontal central regions was predictive of donation behavior. The effect of charity type and emotional priming on the data from this electrode and time window was analyzed with a 2 by 3 ANOVA as with the behavioral data. This analysis revealed a main effect of emotion priming, $F\,(2, 48) = 6.862$, $p = 0.002$, $\eta 2\,p = 0.222$. In addition, the effect of donation target (saving vs. prevention) was marginally significant, $F\,(1, 24) = 4.159$, $p = 0.053$, $\eta 2\,p = 0.148$). Finally, the interaction

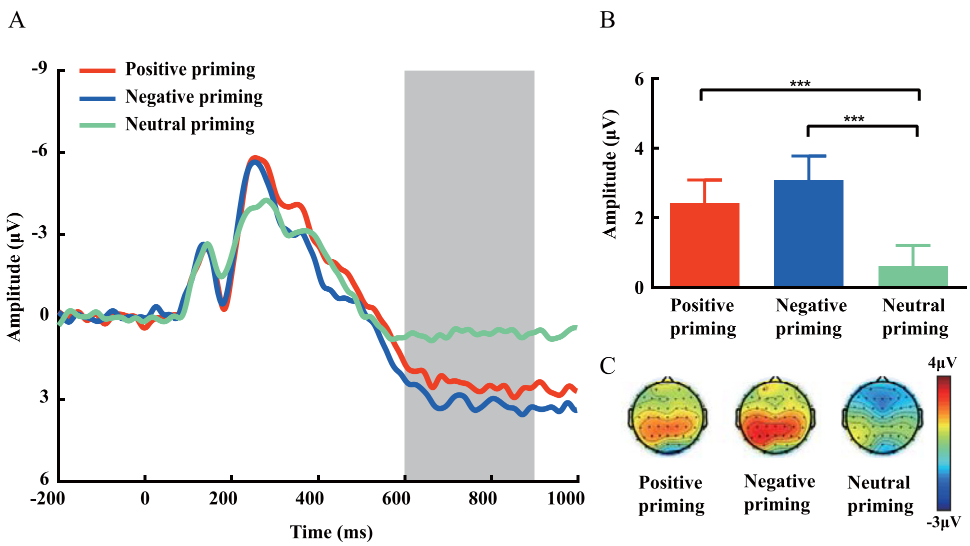

Fig. 6. (A) The LPP waveforms in three different priming conditions at CPz. The gray shaded area shows the analysis window (600–900 ms) in which the LPP was quantified. (B) The mean values of LPP amplitude in each condition, *** $p < 0.001$. (C) Topographic maps for positive / negative / neutral emotion priming (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

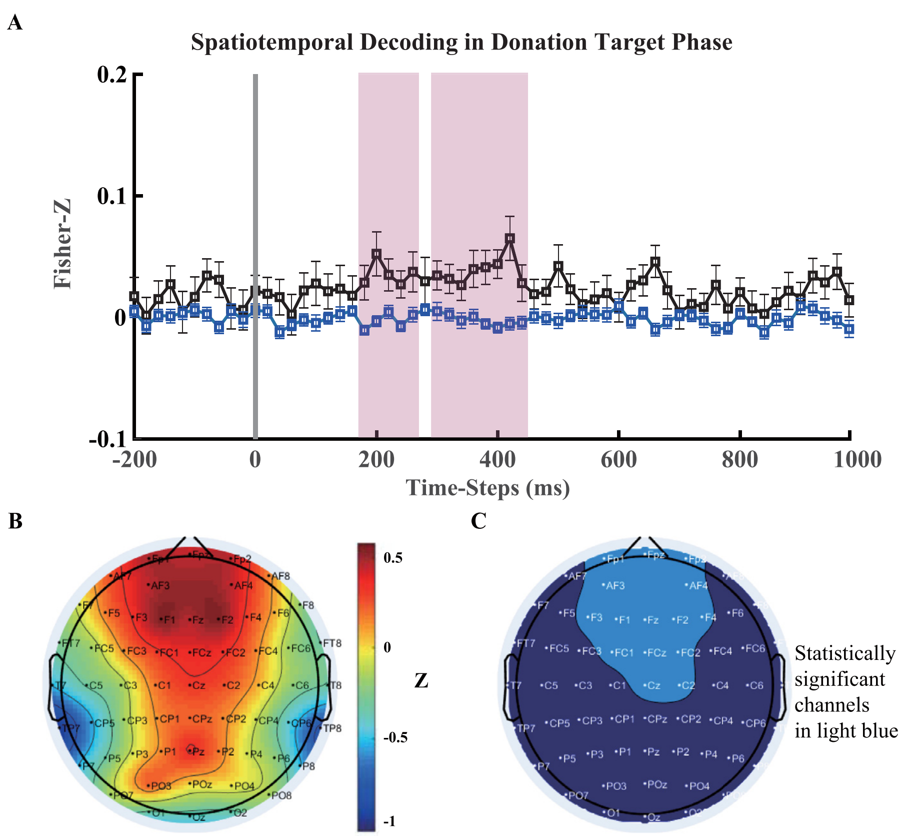

Fig. 7. Donation target phase. (A) Spatiotemporal decoding accuracy across all channels. *Y*-axis represented the Fisher-*Z* score of training data and testing data and *X*-axis showed the time course (step size = 20 ms, window width = 20 ms). The black and blue lines show the actual accuracy and permutation test results respectively. Error bars indicate standard error of the mean. The pink bars indicate the decoding accuracy was significant across these time steps ($p < 0.05$, corrected for multiple comparison). (B) *Z*-standardized absolute feature weights on different channels across time-steps (180–440 ms). (C)Feature weights after corrected for multiple comparison (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

between emotional priming type and donation target was significant, $F(2, 48) = 3.723$, $p = 0.031$, $\eta 2\ p = 0.134$. Simple effect analysis further showed that positive ($M \pm SE$, -9.13 ± 0.83, $p = 0.011$) and negative emotional priming (-9.20 ± 0.84, $p = 0.012$) elicited a larger frontal-midline negativity than neutral emotional priming (-7.78 ± 0.71) in the prevention charity conditions. whereas in the saving charity condition, negative emotional priming (-9.42 ± 0.74) provoked a larger frontal negativity relative to both positive (-7.75 ± 0.83, $p = 0.008$) and neutral emotional priming (-7.53 ± 0.82, $p = 0.002$) (Fig. 9). These results indicate that the neural response to presentation of the donation target was influenced by the previous emotion priming.

4. Discussion

The aim of the present paper was to determine if donation behavior could be predicted on a trial-by-trial basis from spatiotemporal characteristics of the EEG, both on the basis of emotional responses and value computations, and if so, to determine where and when such predictive capacity would manifest. In complement, we investigated how different incidental emotional states would influence donation behavior to charities that varied on the urgency of perceived need. To do so, we first primed participants' emotional states with positive, negative, or neural pictures, and then presented two categories of charities to which

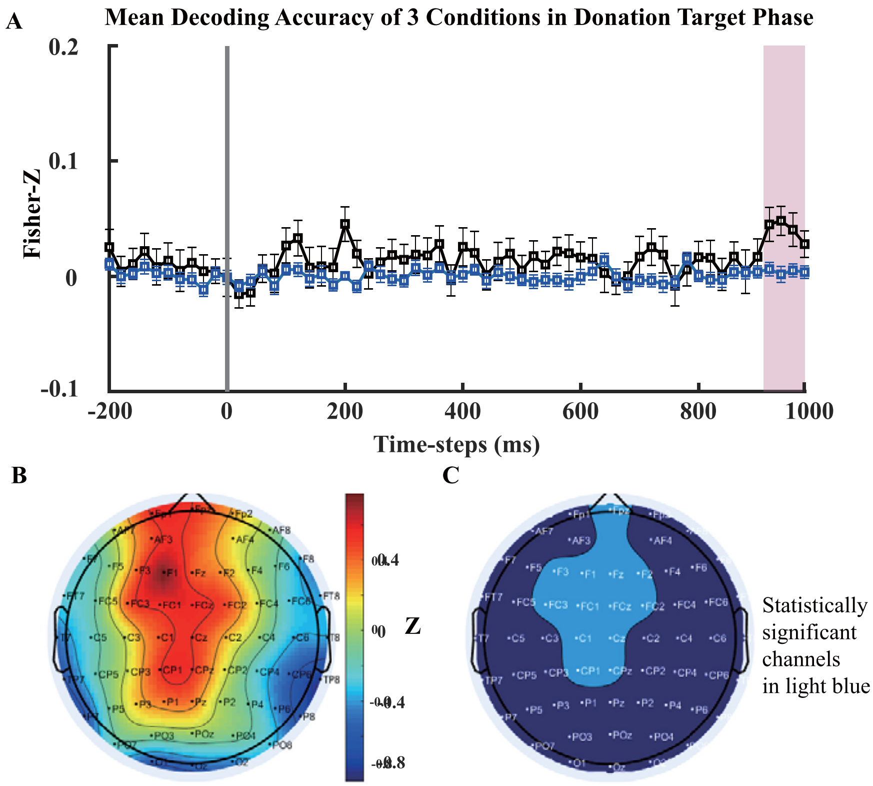

Fig. 8. (A) Mean decoding performance (Fisher-transformed correlation coefficients) across the three emotion conditions separately in the donation target phase. The pink bars indicate the decoding performance on real data was significantly larger than that on randomly re-labelled data in this cluster after multiple comparison correction. Note that the Fisher-*Z* score in this cluster was also significantly larger than zero. (B) *Z*-standardized absolute feature weights on different channels across time-steps (920–1000 ms). (C)Feature weights after correcting for multiple comparisons (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

they could donate: charities saving individuals from current suffering, or charities dedicated to preventing future suffering.

We observed activity in the frontal midline consistent with a source in the MPFC that was predictive of donation behavior between approximately 200 ms and 400 ms after both emotional priming images, and after the charity cue. In addition, emotional priming images elicited EEG activity over more centroparietal midline areas at later time windows (480–560 ms, 800–920 ms) that was also predictive of donation amount. Given that these effects were only observed with the across-condition analysis, we can't be sure if these clusters reflect activity related to value computation, or confounding, irrelevant differences between condition. However, these clusters were broadly consistent with our hypotheses based on previous research, that the MPFC should be directly involved in the value computation that is manifested by the donation amount (*e.g.* Hare et al. 2010; Hutcherson et al., 2015; Tusche et al., 2016), and that later parietal activity should index emotion-related processing that also affects donation behavior (*e.g.* Schupp et al., 2006; Olofsson et al., 2008). When the analysis was conducted within each condition separately to control for potential confounds operating across conditions, activity over the frontal midline between 900 and 1000 ms was predictive of donation amount. This second analysis was free of confounds but may be noisier due to the fewer number of trials. Even so, the cluster identified with this analysis overlapped in time and space with a cluster identified in the across-condition analysis. This cluster may also reflect a value computation in the MPFC, either sustained from earlier processing, or a later commitment to the decision. In any case these findings demonstrate the strength of MVPA analysis of EEG data in this context, reinforce the view that MPFC activity indexes a value computation that translates directly to the size of donations, and illustrate how emotion-related activity over the centroparietal midline may influence donation decisions.

That early frontal-midline activity evoked by the emotional priming images may also be predictive of donation amount was somewhat surprising. If this frontal midline activity reflects value computation in the ventral MPFC as observed in fMRI studies (*e.g.* Hare et al. 2010; Hutcherson et al., 2015, Tusche et al., 2016), it is possible that it's sensitivity to donation behavior in reaction to the emotional priming could be an early assessment of the value of donating based solely on current emotional state, independent of the charity type (knowing the charity cue and subsequent decision is coming). This aligns with donating theories that specify emotional state and mood management as important predictors of donating behavior that are incorporated into valuation of options (*e.g.* Dickert et al, 2011). A second interpretation is that activity in the frontal midline in response to the emotion priming images was not functionally related to the activity in the frontal midline in response to the charity cue. Activity in the frontal midline in response to the emotional priming images was also predictive of donating behavior between 800–920 ms. ERP components sensitive to emotional processing often extend relatively late in time after the eliciting stimulus and are thought to reflect sustained attention to emotional stimuli (*e.g.* Schupp et al., 2006; Olofsson et al., 2008). Thus, the early and late frontal-midline activity together could reflect early and sustained, ongoing attention to the emotional stimuli that would ultimately affect the value computation. It is important to acknowledge that the SVR failed to find information predictive of donation amount in the early time windows when the SVR was run on each condition separately. However, as noted previously, this control analysis should be less powerful due to the reduced number of trials (33%) on which to base the SVR. Thus, we cannot conclude that the early frontal midline activity was driven by value computation, but at the same time, we should not brush the result aside and conclude it was merely due to confounds. It is an effect that awaits replication in future work.

The MPFC often produces negativities in the ERP over the frontal midline (*e.g.* the N2, the error-related negativity, the feedback-related negativity) (Holroyd and Coles 2002, Miltner et al., 1997; Nieuwenhuis et al., 2003). These results beg the question, does the negativity that that appears predictive of donating behavior in this experiment map onto any known components? Perhaps the most likely can-

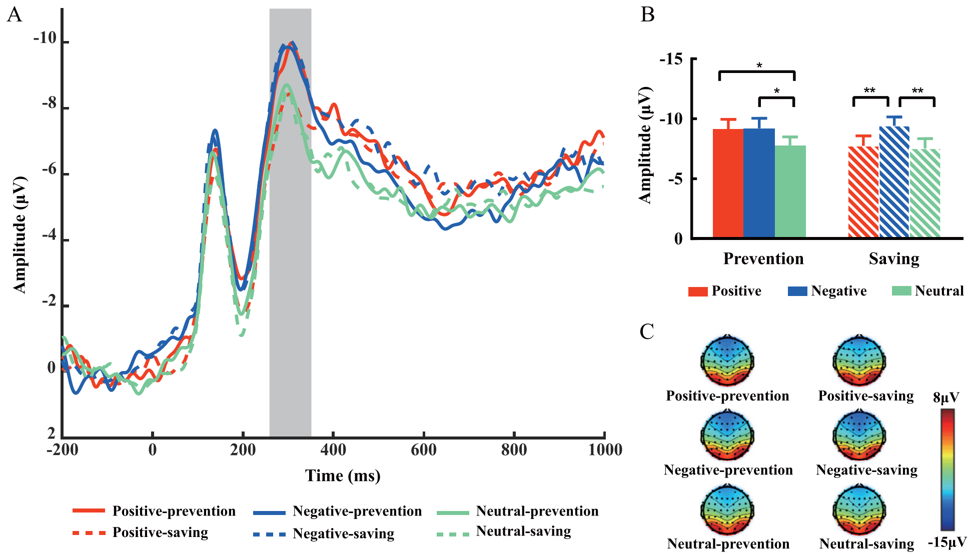

Fig. 9. (A) The grand average waveforms in the donation target presentation phase at FCz. Gray shaded area shows the 260–350 ms analysis window where the frontal midline negativity was quantified. (B) The mean amplitude of the frontal negativity in each condition, $^{*}p < 0.05$, $^{**}p < 0.01$. (C) The topographic maps of frontal negativity effect in the six conditions.

didate is the N2. The N2 is typically maximal at FCz, and peaks between 200 and 400 ms. The N2 is associated with cognitive control (Folstein and Van Petten, 2008; Megías et al., 2017; Nieuwenhuis et al., 2003) as well as outcome valuation (Miltner et al., 1997; Tyson-Carr et al., 2018). The N2 has been source-localized to the medial frontal cortex (Nieuwenhuis et al., 2003). Notably, Warren and Holroyd (2012) suggested that N2 amplitude is modulated by phasic norepinephrine release (see also Mückschel et al., 2017). Norepinephrine is a neuromodulator that increases the reactivity of target neural populations in cortex (Berridge and Waterhouse, 2003; Servan-Schreiber et al., 1990). Phasic norepinephrine release is strongly linked to emotional arousal, and has a strong influence on decision-making (Berridge and Waterhouse, 2003; Nieuwenhuis et al., 2005; de Gee et al., 2017). This interpretation gives arousal-related phasic norepinephrine release a direct, modulating role on value computation in the MPFC.

The conventional ERP analysis revealed a larger EPN and central-posterior LPP elicited by the emotional stimuli than by the neutral stimuli. The ERP results in the priming phase reported here replicate the robust finding that emotional pictures draw more attention and deeper cognitive evaluation than neutral pictures (Schupp et al., 2006; Olofsson et al., 2008; Schindler and Kissler, 2016), suggesting that the priming manipulation was successful. In addition, participants' subjective reports also showed that their emotions were more negative in the negative priming condition. Participants also reported reduced positive emotion in the neutral priming condition, suggesting that the task itself may impair their positive emotion. Correspondingly, this effect weakened the positive emotion priming effect as measured by participants' rating data. However, the positive priming did show a trend that it could reduce participants' negative emotion ($p = 0.087$).

Individuals donated more money after being primed by negative emotional pictures than positive or neutral pictures, and donated more to charities devoted to saving people in current need than to charities devoted to preventing future suffering. These results demonstrate that both subjective emotional states and objective charity types influenced participants' donation behaviors. In line with studies that showed emotional states affect other prosocial behavior (Clark and Waddell, 1983; Shaffer and Graziano, 1983; Gendolla, 2000), we showed that task-unrelated emotion states drive donation amount. The two charity types that we presented here might have influenced "awareness of need", which is an important motivator of donation behavior (Bekkers and Wiepking, 2011). Specifically, 'saving' from current need received greater priority than 'preventing' future need. This work also partly aligns with Sawe and Knutson (2015), who showed that negative emotions provoked by protecting destructive land use in American National Parks motivated donating to prevent the destruction. In contrast, beautiful depictions of the parks themselves elicited positive emotion, but did not increase donating behavior. Notably, Sawe and Knutson (2015) suggested that further research should examine the effect of current need (restoring already-damaged resources) versus future need (preventing future harm), which we have done here, finding that current need is prioritized.

One important limitation of this study is that the experiment was designed to examine the information coded in the EEG related to donation amount as it may manifest across emotional-priming conditions. This method of analysis, coupled with the fact that donation amount varied systematically across conditions, meant that the SVR could achieve some level of accuracy merely by decoding brain activity associated specifically with a condition, not by identifying brain activity associated with the specific donation amount at the single-trial level. A second, within-condition analysis controlled for this limitation, but in doing so lost substantial sensitivity by including far fewer trials in each SVR analysis. However, the frontal-midline showed late activity predictive of donation amount in both analyze, suggesting a reliable effect. Thus, some, but not all, of the SVR results should be treated with caution.

A second limitation to this study is that the positive emotional priming was not significant as measured by self-report. A recent meta-analysis showed that emotional pictures elicit greater negative priming than positive priming (Yuan et al., 2019). Accordingly, negative priming should have been more robust than positive priming in this study because we used images instead of words. Even so, the underlying neural activity suggests that although the positive priming was not significant in the self-report measures, the brain activity was sensitive to the difference. This could mean that the priming effect only lasted a short period, being present during trials, but not during the post-block rating phase. Another possibility is that the pre-task rating of positive affect was quite high, which may have caused the ceiling effect on positive emotion ratings. One final speculation is that positive affect generally declined over the course of the study (in all priming conditions) simply because participating in research studies is often considered a bit arduous. Thus, positive priming may have had to work against a more general decline in positive affect due to time on task, diminishing the reduction in positive affect observed in the other conditions, but not completely overcoming it in the positive prime condition. Without complete evidence of positive emotional priming, we cannot rule out the possibility that the lack of an effect of positive emotion on donation magnitude was simply due to a lack of positive emotion. Thus, positive priming might also promote donation as suggested by several previous studies (O'Malley and Andrews, 1983; Carlson et al., 1988; Bartlett and Desteno, 2006).

5. Conclusion

In summary, we show that EEG activity in response to both emotional primes and charity cues is predictive of donation behavior on a trial by trial basis. In addition, we found that negative mood priming increases donation behavior relative to both neutral and positive mood priming. Finally, we found that the perceived urgency of a charity target (current need vs. future need) increases donation amount as well. We provide additional, cautious support for the role of ventral MPFC in calculating the value of an option in the context of altruistic behavior. We further speculate that noradrenergic modulation of the MPFC may be one mechanism by which emotional arousal may affect activity in the MPFC, and modulate the value computation. This work further validates the application of MVPA to EEG data to provide converging, complimentary evidence in social neuroscience studies. The application of machine learning in this ERP investigation of donation behavior supports a new tool for investigating high level social cognition.

Declarations of Competing Interest

None

Credit authorship contribution statement

Qiuyan Huang: Conceptualization, Visualization, Writing – original draft. **Danyang Li:** Conceptualization, Data curation, Formal analysis. **Can Zhou:** Validation, Writing – review & editing. **Qiang Xu:** Formal analysis, Visualization. **Peng Li:** Conceptualization, Formal analysis, Funding acquisition, Writing – review & editing. **Christopher M. Warren:** Conceptualization, Supervision, Writing – review & editing.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.neuroimage.2021.118475.

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