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RESEARCH ARTICLE

Differential neural processing of reward and self-relevance in a social gambling paradigm

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Abstract

We preferentially process self-related information. However, less is known about how this advantage extends to reward processing and if this process is sensitive to a continuum of self-relevance. Specifically, do we dissociate ourselves from all others when processing rewards, or do those we know personally also enjoy self-related biases? To address this, we recorded electroencephalographic (EEG) data from 30 undergraduate student participants who played a simple two-choice "bandit" gambling game where a photo presented before each gamble indicated whether it benefited either the participant, an individual they knew, or a person they did not know. Temporal spatial principal components analysis (tsPCA) of EEG data evoked by target photos revealed a component consistent with attention and early perceptual processing (the P200), while analysis of data evoked by the feedback stimuli revealed a component consistent with reward processing (the reward positivity). Results demonstrated that P200 component scores were larger for self-gambles than both known- and unknown-other target photos. Interestingly, and contrary to previous findings, reward positivity component scores were similar for all gambles independent of perceived ownership. Our findings suggest that, when gambling for individuals on a continuum of self-relevance, the potential for monetary gain based on the self-relevance cues is differentially processed for ourselves while the actual reward is not. We suggest that the known-other gambling target introduced an empathy-like effect, contesting the self-bias in reward processing.

Keywords Self-relevance · Electroencephalography · Reward processing

Introduction

Humans tend to be biased toward information relevant to themselves. Some posit that we are inherently self-preservative, and our behaviour reflects the desire to maximize utility (Cunningham et al., 2013; Mill, 1863). Another possibility is that we find self-relevant information inherently rewarding and bias cognition accordingly (Northoff & Hayes, 2011). Either way, stimuli related to our sense of self are differentially processed throughout the brain, including attention (Alexopoulos et al., 2012; Humphreys & Sui, 2015; Keyes & Dlugokencka, 2014; Turk et al., 2011), perception (Sui & Humphreys, 2015; Sui et al., 2012, 2014), memory (Cunningham et al., 2008, 2011), and learning (Hassall et al., 2016; Krigolson et al., 2013).

Biased attentional and perceptual processing of self-relevant information is a robust psychological phenomenon. Both auditory and visual stimuli are attended to more rapidly when associated with our sense of self (Bargh, 1982; Moray, 1959; Sui et al., 2006; Wolford & Morrison, 1980; Yang et al., 2013). Furthermore, self-relevant stimuli yield similar advantages in perceptual processing (Keyes & Dlugokencka, 2014; Keyes et al., 2010), even when self-relevance is associated with novel stimuli (Sui et al., 2012). Biases in attention and perception are also evident in studies employing electroencephalography (EEG), where event-related potential (ERP) components indexing these processes are sensitive to a stimuli's relatedness to self (Fan et al., 2013; Fields & Kuperberg, 2015; Sui et al., 2006; Turk et al., 2011). Attention to names with high self-relevance elicits larger N200, P200, and P300 amplitudes (Fan et al., 2013). Cues that an object belongs to someone elicit a smaller P100 (Turk et al.,

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2011) and larger P200 (Krigolson et al., 2013) than unowned objects. Of particular importance is a previous finding that the P200, a medial-frontal ERP component maximal around 200–300 ms after stimulus presentation, was larger for cues that indicated an upcoming, reward-related decision was self-relevant (Krigolson et al., 2013). It was hypothesized that this component reflected the medial-frontal reward system processing the potential for gain present in self-related but not other-related trials. Taken together, evidence suggests that self-related information is preferentially attended to and perceived for importance, perhaps to the benefit of later cognitive processes.

Another cognitive process affected by self-relevance is reward processing. For example, the reward positivity is an ERP component that is maximal when feedback indicates an outcome is better than expected (Krigolson, 2018; Proudfit, 2015; Williams et al., 2017). The reward positivity is calculated as the difference in neural responses to win and loss feedback in reinforcement learning tasks and is thought to reflect positive prediction errors calculated in the medial-frontal cortex (Holroyd & Coles, 2002; Holroyd & Yeung, 2012; Krigolson, 2018). When reinforcement learning tasks are manipulated so that outcomes benefit the player or an unknown other, the reward positivity is larger for self-related rewards than other-related rewards (Hassall et al., 2016; Krigolson et al., 2013). However, it is still somewhat unclear how the reinforcement learning system differentiates known others, such as close friends, from unknown others (i.e., strangers). Would this reinforcement learning system also preferentially process rewards for someone we know, or would they be treated as an "other?".

The goal of the present experiment was to extend previous work on self-relevance and neural indices of reward learning. Specifically, we sought to determine if reward learning systems are sensitive to familiar and unfamiliar others, suggesting they track self-reference on a continuum. To accomplish this, we had participants play a gambling task where each gamble benefitted themselves, someone they know personally, or a stranger. In this task, participants select one of two coloured squares resulting in a win or a loss, where one square has a higher probability of resulting in a win while EEG was recorded. Before each choice, a photo and the name of the participant, their known other, or the unknown other (i.e., the stranger) was shown before the decision to indicate who would benefit from the subsequent gamble. "Win" feedback on a decision would result in a monetary reward for that person. As such, this approach yields two areas of analysis: attentional and perceptual ERPs yoked to the presentation of the target cue (P200) and a reward learning ERP linked to the presentation of performance feedback (reward positivity). First, we hypothesized that the P200 elicited by the presentation of the target photo for the upcoming gamble would be largest for self-gambles, but larger still for known-other gambles than stranger-gambles, in line with previous examples of self-bias in attention, perception (Fan et al., 2013; Sui et al., 2006), and reward processing (Krigolson et al., 2013). We posited that a similar relationship would be present for the reward positivity elicited by the feedback presented after each gamble, given the existing advantage of the self in reward processing (Hassall et al., 2016; Krigolson et al., 2013). The proposed pattern of results would indicate that we process reward-related information on a scale of self-relevance, even when the outcomes do not benefit us directly.

Methods

Participants and materials

Thirty undergraduate students (7 males, 23 females; mean age 21.4 years old [95% confidence interval [CI] 20.4, 22.4]) from the University of Victoria were recruited to participate in this study. Participants volunteered either through the University of Victoria's online research participation system or through paper ads posted around the University of Victoria campus and were compensated for volunteering with either psychology course credits or cash, respectively. Before commencing the experiment, all participants provided informed consent in agreeance with the guidelines established by the University of Victoria Human Research Ethics Board (Ethics Protocol Number: 20–1512) and followed the ethical standards specified in the 1964 Declaration of Helsinki.

Before participants arrived in the laboratory to complete the experiment, they were asked to provide information about themselves and someone they knew personally. We asked that the participants receive verbal consent from the known-others before providing information about them for the study. Participants provided photographs of themself and the person they identified as a known-other, that individual's name, and the participant's relationship to that individual (e.g., friend, significant other, family member; Table 1). Participants were given a sample photo from a photo database used in the experiment to match their expression and position (neutral expression portrait, showing the top one-quarter of the torso to the top of the head with a blank, medium-lit background). Finally, we asked for the contact information

Table 1 Descriptive statistics for IoTS scale scores

	M	SD
Close friend ($n=11$)	4.9	±1.0
Significant other ($n=7$)	5.6	±1.3
Family member ($n=12$)	5.9	±0.9
All	5.5	±1.1

of the participant's known-other to obtain their consent to be included in the study and reimburse them after the study.

To assess relatedness between the participant and the colleague, we used the Inclusion of the Other in the Self scale (IOtS scale; Aron et al., 1992). The IOtS scale has participants select from a set of seven pairs of circles with varying overlap (the first pair is not overlapping at all; the seventh pair is almost entirely overlapped; Fig. 1). Participants were asked, "Which picture best describes your relationship with [the colleague's name]?" and to input the corresponding number.

Apparatus and procedures

Participants were first prompted with the name and photograph of the colleague whom they identified. Next, they were asked to complete a computerized version of the IOtS scale described before starting the experiment.

Following this, participants completed a modified computer version of a two-armed bandit task (Sutton & Barto, 2018; Fig. 2) in a sound-dampened room in which EEG data were recorded. During the performance of the two-armed bandit task, participants completed a series of gambles by selecting between one of two coloured squares presented on a standard 19″ LCD monitor. Participants were given two blocks of practice trials without reward and with altered probabilities to familiarize themselves with the task. In a key manipulation, participants were tasked with making gambles for one of three individuals with varied relatedness to them: self, known-other, and stranger. Before each trial, a photo and name appeared indicating who the participant was gambling for. Participants were instructed that each "winning" decision would yield a monetary reward for that individual. For example, if a trial began with a "known-other" stimulus (in Fig. 2, the known-other is someone named "Isaiah") and the participant won, the participant's known-other would receive money. As such, we instructed participants that their goal was to win as much money as possible for each of the three people in the experiment (themselves, their known-other, and the stranger).

Each trial began with a fixation cross, followed by the presentation of a photo and name corresponding to one of the three gambling targets. In the "You"-targeted trials, the photo of the participant appeared in the centre of the screen with the word "YOU" above it. On the "Known-Other" trials, the photo of the colleague identified by the participant appeared in the centre of the screen with the colleague's name above it ("ISAIAH"). Finally, in "Stranger" trials, a photo of an individual was randomly selected from the Color FERET Database (National Institute of Standards and Technology (NIST), 1996), with the word "STRANGER" above it. The photo stimulus appeared for 1000 ms. Next, a white fixation cross was presented, followed by two-coloured squares that appeared onscreen for an additional 500 ms. Next, a change in the colour of the fixation cross from white to grey (RGB: [128 128 128]) signalled participants to select one of the two squares by using a computer gamepad. Participants had up to 2000 ms from this point to make a selection. Following the selection of a square, both squares disappeared, and a white fixation cross appeared. After this, a feedback symbol indicating the outcome of the trial ($ for a win, 0 for a loss) appeared in place of the fixation cross for 1000 ms. Fixation crosses that appeared before and after face presentation, and after a square was chosen were

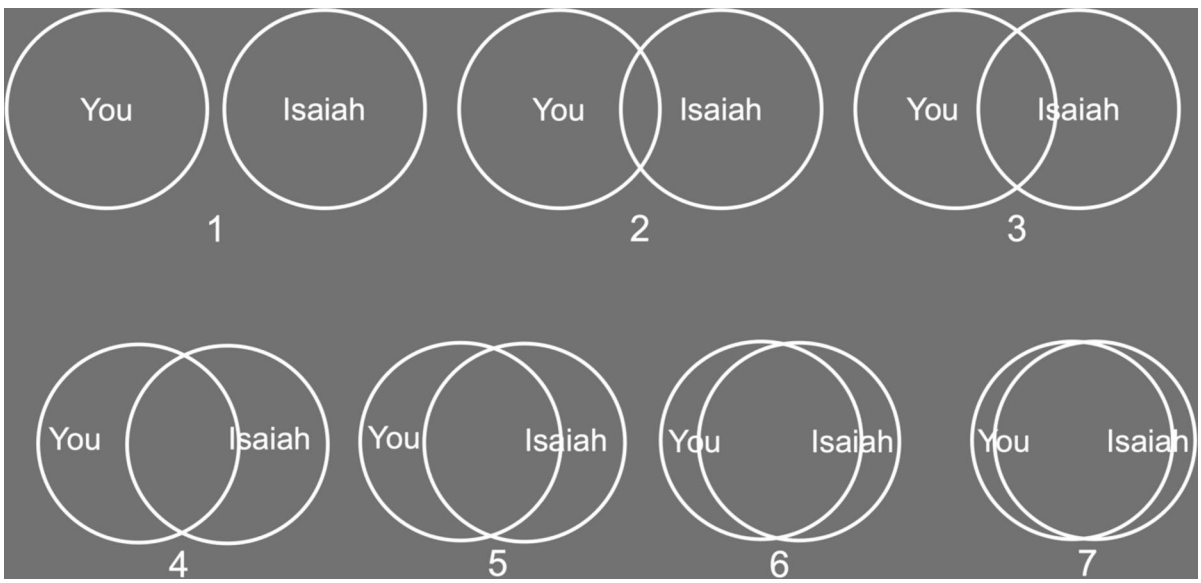

Fig. 1 Example of the IOtS scale presented to participants before the experiment. The participant identified a known-other named "Isaiah"

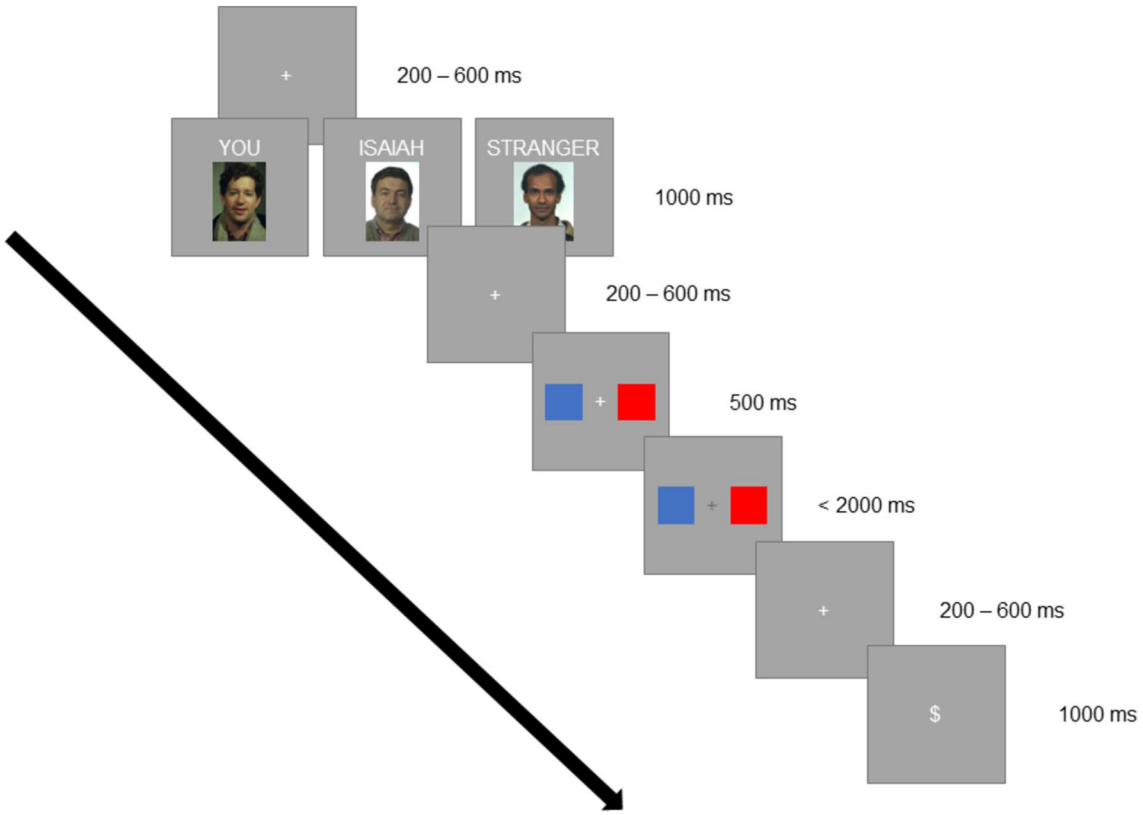

Fig. 2 Example of a single trial of the modified bandit task. The outcome was a "win, so a "$" symbol appeared at the end of the trial

jittered from 200 to 600 ms. The next experimental trial began immediately after the offset of the feedback stimulus. Based on previous work in our laboratory (Colino et al., 2020; Hammerstrom et al., 2021; Howse et al., 2018; Krigolson et al., 2017), one square colour had a higher probability of winning than the other square colour (60% vs. 10%) to ensure an approximate number of win and loss trials per participant. Importantly, these percentages also make the task learnable (i.e., one square won more often than the other so there was an optimal choice on each trial) and ensure a win/loss rate of roughly 50% to avoid frequency contamination of the N2 (Holroyd, 2004).

Unbeknownst to participants, each win earned 10 cents. At the end of the experiment, the participant was given cash based on their performance in the You trials (M = $5.03, [95% CI $4.77, $5.28]), and their colleague was sent an electronic gift card based on the participant's performance in Known-Other trials (M = $4.98, [$4.74, $5.22]). After the completion of the experiment, we debriefed the participants by informing them that the Stranger was a fictional entity created for the study and that they would not receive money (unrealized earnings: M = $4.68, [$4.31, $5.06]).

The experiment consisted of 15 blocks of 20 trials, with each trial corresponding to one of the three conditions. The three conditions were randomized trial-to-trial but equally distributed throughout the experiment so that there were 100 trials for each condition. The task was programmed in MATLAB (Version 9.6, Mathworks, Natick, USA) using the Psychophysics Toolbox extension (Brainard, 1997), and participants used a ResponsePixx (VPixx Technologies) button box to make their selection.

Data acquisition

Response time (ms), outcome (win or loss), and accuracy (selection of the square with the higher win probability) were recorded by the MATLAB (Version 9.6, Mathworks, Natick, USA) experiment script. EEG data were collected from 64 active electrodes, mounted in a 10–20 layout fitted cap (ActiCAP, Brain Products GmbH, Munich, Germany), using Brain Vision Recorder software (Version 1.21, Brain Products GmbH). All electrodes were referenced to electrode AFz during recording, and impedances were always maintained below 20 kΩ. EEG data were recorded at a sampling rate of 500 Hz, amplified (ActiChamp, Revision 2, Brain Products GmbH, Munich, Germany), and filtered through an antialiasing low-pass filter of 245 Hz.

Data analysis

Behavioural data analysis

For all three conditions, we computed each participant's mean response time, outcome ratio, and accuracy rate. The response time was calculated as the mean time it took for participants to select one of the squares using the button box after the fixation cross turned grey, signalling when the participant was permitted to respond in each block. The outcome ratio was calculated as the percentage of all valid trials (excluding early responses or responses made with an invalid button) within a condition (You, Known-Other, or Stranger) that resulted in "Win" feedback for the participant. Finally, we calculated accuracy as the proportion of trials in each condition that the participant selected the square with the higher probability of winning.

EEG data pre-processing

All EEG data were processed using MATLAB (Version 9.6, Mathworks), using the EEGLAB open-source toolbox (Delorme & Makeig, 2004) and custom software developed in the Krigolson Laboratory (available at: https://github.com/neuro-tools). First, channels were visually inspected for noisy data and removed accordingly (M = 0.8 channels, [0.5, 1.1]). Continuous EEG data were then re-referenced to mastoid channels (TP9, TP10). Next, channels that were removed were reinterpolated using the method of spherical splines. A dual-pass phase-free Butterworth filter with a band-pass of 0.1 Hz to 30 Hz and a 60-Hz notch filter was applied to the re-referenced EEG data. To identify and remove ocular artifacts, an independent component analysis (ICA) was conducted on the filtered data to identify components associated with ocular artifacts (Delorme & Makeig, 2004). Visual examination of the ICA factor loadings, as well as cross-correlations between EEG data and ICA component activations, guided the selection of components that contained eye blinks and movements so that they could be removed. Following the removal of components that were associated with ocular artifacts, the EEG data were reconstructed from the remaining ICA components.

All data were segmented by condition and feedback outcome (win or loss) into shorter epochs spanning from − 200 ms to 600 ms after the stimulus presentation. The segments were then baseline-corrected by using the 200-ms window before feedback onset. Segments were next examined for artifacts, and segments of data containing a gradient larger than 10 μV/ms or segments with an absolute difference of more than 150 μV were removed, which resulted in an average of 13.84% [9.92%, 17.76%] of data being lost across participants.

ERP Component analysis

Following artifact rejection, ERPs were created by averaging the segments across all trials for each of the three experimental conditions (You, Known-Other, or Stranger) for the face cues (presentation of gambling target) and the two gamble outcomes (Win or Loss), resulting in nine ERP waveforms.

To identify ERP components, we submitted the ERP data to a temporospatial Principal Components Analysis (tsPCA; Dien, 2012; Dien et al., 2003; Foti et al., 2009) using custom MATLAB code and the EP Toolkit (Dien, 2010b). The temporal data were submitted to a PCA with a Promax rotation. Visual inspection of the resulting temporal factors guided the selection of a factor with latencies matching our ERPs of interest (Dien, 2010a, 2012). The data for these temporal factors were then reshaped with topography (channel) as the independent variable and were submitted to a spatial PCA with Varimax rotation. Factor loadings from the resultant temporospatial component pairs were compared between conditions. For the P200, we examined components evoked by the face cue, whereas for the reward positivity, we examined components evoked by the difference between Win and Loss feedback (Foti et al., 2011). The resultant temporospatial component loadings were compared between conditions.

Statistical analysis

We submitted our behavioural measures (response time, outcome percentage, and accuracy) and ERP components of interest to one-way (condition: You, Known-Other, Stranger) repeated-measures ANOVAs (RM ANOVA). Mauchly's test for Sphericity was computed for all ANOVAs, and if sphericity was violated, Greenhouse–Geisser values were reported. Furthermore, we examined planned comparisons between You and Known-Other trials and Known-Other and Stranger trials with pairwise *t*-tests. ANOVAs were analysed post-hoc with Bonferroni corrections to compare the You and Stranger trials. Next, to determine if the reward positivity scales with relatedness, we compared component loadings in the known-other condition and to the IOtS score the participant gave for their friend at the beginning of the experiment with Pearson's R correlation. All statistical operations were conducted in R via R Studio (Version 2022.07.2, R Core Team), and significance levels for all tests were set at $\alpha = 0.05$.

Results

Behavioral results

IoTS Scale. Results from the IoTS scale presented to participants, separated by relationship category, are presented in Table 1.

General Performance. Participants selected the square with a higher probability of providing a Win an average of 75.33% [71.02%, 79.66%] of all experimental trials. Furthermore, we found that participants were selecting the higher probability square more often than chance, $t(29) = 12.014, = p < 0.001$, $d = 2.854$, indicating that they did learn the task. One-way RM ANOVAs with three levels (condition: You, Known-Other, Stranger) were applied to all behavioural measures.

Response Time. Mauchly's test indicated the assumption of sphericity had been violated for response time, so Greenhouse–Geisser corrected tests were reported ($\epsilon = 0.64$). Reaction time did not differ between conditions, $F(1.51, 43.73) = 0.74$, $p > 0.05$, $\eta_g^2 = 0.00$ (Fig. 3).

Outcome. The RM ANOVA examining outcome rate revealed no main effect of condition, $F(2, 58) = 0.8$, $p > 0.05$, $\eta_g^2 = 0.08$.

Accuracy. Mauchly's test indicated the assumption of sphericity had been violated for accuracy data, so Greenhouse–Geisser corrected tests were reported ($\epsilon = 0.59$). Finally, the RM ANOVA examining accuracy revealed a main effect of condition, $F(1.19, 34.37) = 7.87$, $p < 0.01$, $\eta_g^2 = 0.213$. Planned comparisons demonstrated no difference between Known-Other and You trials, $M_D = -1.07\%$ [−3.64%, 1.51%], $t(29) = -0.846$, $p > 0.05$, $d = -0.08$, but a difference between Known-Other and Stranger trials, $M_D = 9.43\%$ [3.83%, 15.0%], $t(29) = 3.443$, $p < 0.001$, $d = 1.11$. Bonferroni post-hoc tests revealed a difference between You and Stranger conditions, $M_D = 8.37\%$ [1.51%, 15.23%], $t(29) = 2.113$, $p < 0.05$, $d = 0.66$.

ERP results

Component analysis linked to the photo stimuli yielded tsPCA components similar in timing and topographies to the P200 (Fig. 4). The full results of the tsPCA on photo stimuli waveforms are presented in the Supplementary Materials.

P200. Temporal PCA revealed a component consistent with the timing of the P200 accounted for 54.02% of the observed temporal variance, and subsequent spatial PCA yielded a primarily frontal topography accounting for 41.60% of the observed spatial variance (Fig. 4). A one-way RM ANOVA revealed an effect of condition on component loadings for the P200 component, $F(2, 58) = 16.615$, $p < 0.001$, $\eta_g^2 = 0.056$. Planned comparisons demonstrated a difference in P200 scores between You and Known-Other trials, $M_D = 0.416$ [0.211, 0.621], $t(29) = 4.150$, $p < 0.001$, $d = 0.76$, but not between Known-Other and Stranger trials, $M_D = 0.139$ [−0.094, 0.372], $t(29) = 1.222$, $p > 0.05$, $d = 0.22$. A Bonferroni post-hoc test revealed a difference in P200 scores between You and Stranger conditions, $M_D = 5.55$ [3.08, 8.02], $t(29) = 5.540$, $p < 0.001$, $d = 0.57$.

Reward positivity. Temporal PCA of ERPs linked the difference between win and loss feedback revealed a component consistent with the timing of the reward positivity that accounted for 9.06% of the observed variance, and subsequent spatial PCA yielded a primarily frontal topography accounting for 43.46% of the observed spatial variance (Fig. 5). Statistical analysis revealed no effect of condition, $F(2, 58) = 0.486$, $p > 0.05$, $\eta_g^2 = 0.016$ (Fig. 5). Further analysis of correct feedback and incorrect feedback revealed PCA components with similar timings and topographies, likewise yielding no effect of condition, win: $F(2, 58) = 0.320$, $p > 0.05$, $\eta_g^2 = 0.011$, loss: $F(2, 58) = 0.932$, $p > 0.05$, $\eta_g^2 = 0.031$. Traditional analysis (i.e., from grand average difference waveforms) is presented in the Supplementary Material.

Additionally, we sought to determine whether the reward processing for Known-Other trials was associated with IOtS

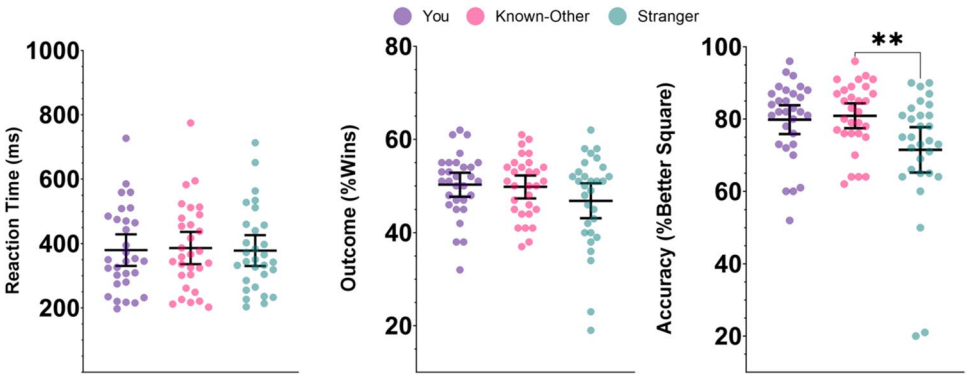

Fig. 3 Behavioural performance outcomes for the three conditions. The horizontal black lines correspond to the mean, and the inner and outer boxes correspond to one standard deviation and 95% within-subjects confidence intervals, respectively. $^{**}p < 0.01$

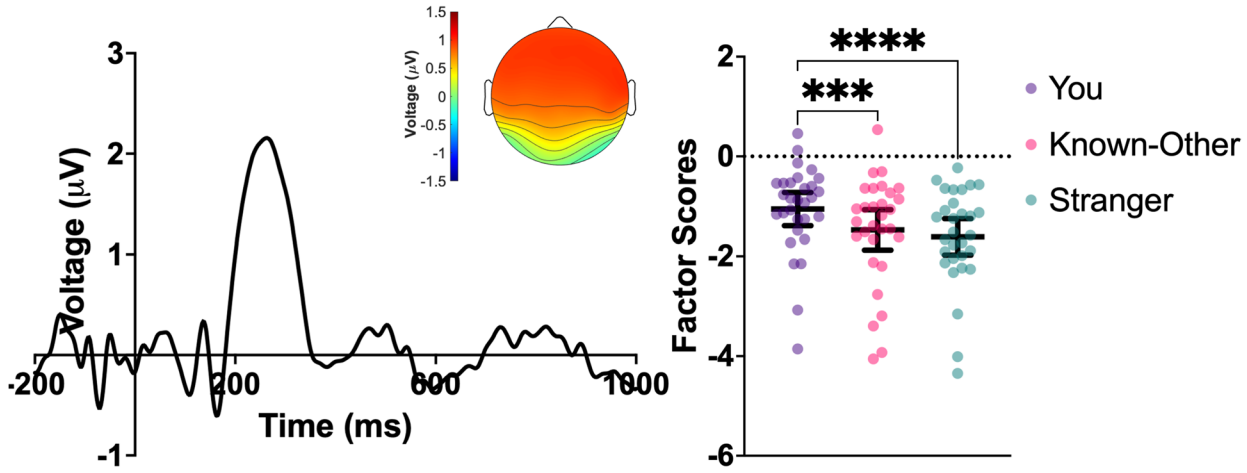

Fig. 4 The tsPCA component consistent with the timing (left) and topography (middle) of the P200. Combined factor scores for the three different conditions are shown on the right, where the middle black lines correspond to means and the error bars represent 95% within-subjects confidence intervals. ***$p < 0.001$; ****$p < 0.0001$

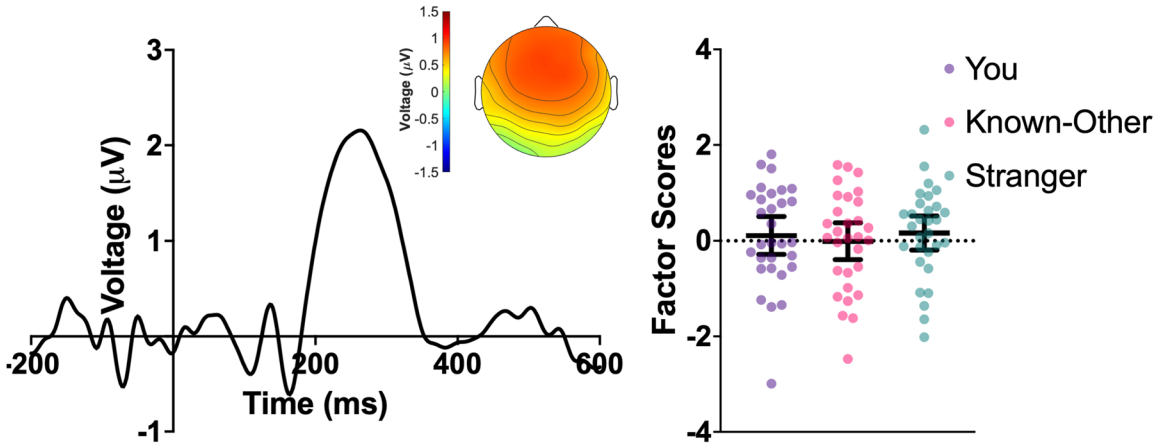

Fig. 5 The tsPCA component consistent with the timing (left) and topography (middle) of the reward positivity. Combined factor scores for the three different conditions are shown on the right, where the middle black lines correspond to means and the error bars represent 95% within-subjects confidence intervals

scale scores. We found that the amplitude of the reward positivity was not significantly correlated to IOtS scores, $r = 0.123$ [−0.248, 0.463], $p > 0.05$.

Discussion

The current study was designed to investigate the impact of self-relevance on the attentional, perceptual, and reward-learning correlates of gambling. Behaviourally, participants performed better when gambling for themselves and friends compared with others, evident from differences in the proportion of trials where the correct square was chosen. The amplitude of the P200 elicited by face cues demonstrated differences between oneself and known-others, but not between known-other and strangers. However, contrary to our hypothesis, reward positivity amplitude was unaffected by trial type. Our results suggest that reward processing is unaffected when known-others are introduced, while perception is biased towards the self in a gambling task. In summary, these results conflict with a large body of work on behavioural and neural indices of self-relevance.

Previous work has demonstrated differences in attentional ERP components between self and other cues. Similar to the current study, Krigolson et al. (2013) demonstrated larger P200 amplitudes for self-related cues compared with unknown-other cues in a reward learning task, which they described as a difference in potential for gain. Comparably, when participants play simultaneously with computer-generated others in a lottery task, there is

an increase in P200 amplitude when they see their performance is different from others' (Luo et al., 2015). The current results affirm this idea, as known- and unknown-other trials (i.e., no monetary gain for the participant) both had reduced P200 components compared to self-trials. An alternative explanation for this effect is that the saliency of self-relevant stimuli (in this case, the face photo) is driving effects beyond the cognitive process of interest. We contend that, because there is no evidence of an N170 component in the conditional tsPCA analysis of photo cues (Supplementary Material), the repeated presentation of face cues equally throughout the experiment would wash out any saliency effects in this context. Our results support existing literature indicating that ERPs elicited by gambling-related cues are biased towards self-relevant stimuli.

Interestingly, we were not able to replicate previous findings from reward experiments that examine self-relevance. Previously, rewards for unknown-others elicited reduced reward positivity amplitudes, a finding that we did not replicate (Hassall et al., 2016; Krigolson et al., 2013). Similarly, in Chinese individuals, the reward positivity is similar when gambles benefit the participants or their parents but larger than when gambling for friends or strangers (Zhu et al., 2015, 2016), although this effect may be culturally dependent (Zhu et al., 2007). Interestingly, self-biases in the amplitude of the reward positivity can be removed if participants are primed with stories using interdependent pronouns (e.g., we, ours) compared with independent pronouns (Zhu et al., 2020). As such, showing more descriptive target information (i.e., a picture and label for each condition) may have created more "realistic" gambling conditions than self-related cues in previous studies (e.g., the labels You and Other; Hassall et al., 2016; Krigolson et al., 2013), priming the participant to show empathy towards the known- and unknown-others. In this case, where the objective value of the reward (i.e., 10 cents) is the same across conditions, introducing targets on a continuum of self-relevance may similarly level out the subjective value of the reward (i.e., someone gained 10 cents), leading to similar reward processing across conditions. Given this, we propose that using realistic representations of known- and unknown-others (i.e., a photo) reduces the self-related bias in reward processing. An alternative explanation is that rather than an effect of empathy, our instructions to win as much as possible for all parties involved in the task could have simply increased the saliency of nonself rewards.

In summary, the current results depict an intriguing impact of self-relevance on reward processing, attention, and perception. While self-related gambling cues elicit larger P200 amplitudes, this self-relevance effect is wiped out for the reward positivity. It seems that introducing a familiar other and more descriptive target stimulus may reduce the self-bias in the processing of rewards, effectively creating empathy towards others in the task. Future work should explore this potential empathy effect by varying how self-related cues are presented to examine how and why known-others may affect reward processing.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.3758/s13415-024-01247-z.

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Author's contributions All authors contributed to study conception and data interpretation. Design of the study, data collection, behavioural, and EEG data analysis were performed by Mathew Rocha Hammerstrom. Post-processing of EEG data (temporospatial PCA) was performed by Dr. Gordon Binsted. Statistical analysis and supervision were performed by Dr. Olave Krigolson.

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Availability of data and materials None of the data or materials for the experiments reported here is available, and none of the experiments was preregistered.

Code availability As per Sect. 2.4.2., EEG analysis was completed with custom software (https://github.com/neuro-tools) derived from EEGLAB (Delorme & Makeig, 2004).

Declarations

Ethics approval The work presented here was approved by the University of Victoria Human Research Ethics Board via Ethics Protocol Number: 20–1512.

Consent to participate Before commencing the experiment, all participants provided informed consent in agreeance with the guidelines established by the University of Victoria Human Research Ethics Board and followed the ethical standards specified in the 1964 Declaration of Helsinki.

Consent for publication Participants were able to indicate whether they wished to participate solely as an observer, rather than have their data included in the publication. None of the participants in this study chose this option, and thus they were all included in the publication.

Open practices statement None of the data or materials for the experiments reported here is available, and none of the experiments was preregistered.

Conflicts of interest/Competing interests The authors have no relevant financial or nonfinancial interests to disclose.

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