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Brain responses in evaluating feedback stimuli with a social dimension

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Previous studies on outcome evaluation and performance monitoring using gambling or simple cognitive tasks have identified two event-related waveforms, albeit in a delayed 300–380 ms

the initial judgment eliciting more negative-going responses than faces consistent with the judgment. However, the ERP waveforms did not show the typical pattern of P300 responses. With the principal component analysis (PCA), a clear pattern of P300 effects *were* revealed, with the P300 being more positive to faces consistent with the initial judgment than to faces inconsistent with the judgment, and more positive to attractive faces than to unattractive ones. The effect of feedback consistency did not interact with the effect of attractiveness in either the FRN or P300 component. These findings suggest that brain responses involved in processing complex feedback stimuli with a social dimension are generally similar to those involved in processing simple feedback stimuli in gambling or cognitive tasks, although appropriate means of data analysis are needed to

previous judgment or expectancy stored in memory against the feedback faces were from the same category. Different pseudo-random orders were created for different participants. Unknown to the participants, the blurred face in each trial was not the same one as the feedback face. The purpose of this manipulation was to exclude the potential influence of the blurred faces on the perceptual processing of the subsequent feedback faces as well as to make sure that about half of the trials would constitute “consistent” trials.

PROCEDURES

Participants were seated in a sound-attenuated, electrically shielded chamber approximately 1 m from a computer screen. At the start of each trial, at the center of the computer screen, a white fixation cross ($0.6° \times 0.6°$ in visual angle) was presented against a black background for 500 ms. Then a blurred black-and-white face photo was presented ($6.3° \times 4.6°$), and remained on the screen until the participant's response (**Figure 1**). The participants' task was to make a binary attractiveness judgment as quickly as possible, by pressing a key on a joystick using their left or right index finger. Button assignment was counter-balanced between participants. After the response, a fixation cross was presented again for 800 ms. Then a unblurred face photo ($6.3° \times 4.6°$), serving as feedback to the participants' initial judgment, was presented for 800 ms, and participants were asked to simply watch it and wait for the next trial. After the unblurred face, a fixation cross was presented for 700 ms and the screen turned black for 100 ms before the next trial began.

Before the EEG test, participants completed a practice block algorithm which employs a regression analysis in combination with artifact averaging (Semlitsch et al., 1986). Epochs contaminated by blinks and other movement artifacts were excluded from averaging using an 80 μV criterion. The EEG data were low-pass filtered at 30 Hz and were baseline-corrected by subtracting the average activity of that electrode during the baseline period from each trial. After excluding trials with artifacts, each participant had at least 46 trials in each condition.

The grand-average ERP waveforms (**Figure 2**) did not show a typical pattern for ERP responses that were observed for feedback stimuli in gambling or simple cognitive tasks (e.g., no clear P300 component was visible), although it appeared that inconsistent faces elicited negative-going deflections in the 300–380 ms time window. We, therefore, analyzed ERP responses in different conditions in the windows of 150–220 ms (i.e., P200), 300–380 ms (i.e., FRN), and 380–500 ms based on visual inspection. For the purposes of statistical analysis, mean amplitudes for each time window was calculated across 25 electrode locations (F3, F1, Fz, F2, F4, FC3, FC1, FCz, FC2, FC4, C3, C1, Cz, C2, C4, CP3, CP1, CPz, CP2, CP4, P3, P1, Pz, P2, P4) that were chosen to cover scalp areas known from previous studies to be the focus of the FRN and P300. A repeated-measures analysis of variance (ANOVA) was conducted, with attractiveness (attractive vs. unattractive), feedback consistency (consistent vs. inconsistent), anterior-posterior scalp location (frontal, frontocentral, central, centroparietal, parietal), and lateral scalp location (left, left central, midline, right central, right) as four within-subjects experimental factors. The Greenhouse-Geisser correction for violation of the ANOVA assumption of sphericity was applied in all analysis. Bonferroni corrections were used for multiple comparisons.

Given that the processing of the feedback faces and their attractiveness was likely to involve sophisticated neurocognitive processes, it is possible that the FRN and the P300 components were not only overlapping in the time course, but also masked by other cognitive (and emotional) processes associated with the complex feedback stimuli. To examine whether the typical P300 effects that were observed in previous studies for various aspects of the outcome evaluation could also be observed for the more complex feedback faces, we performed principal-component analysis

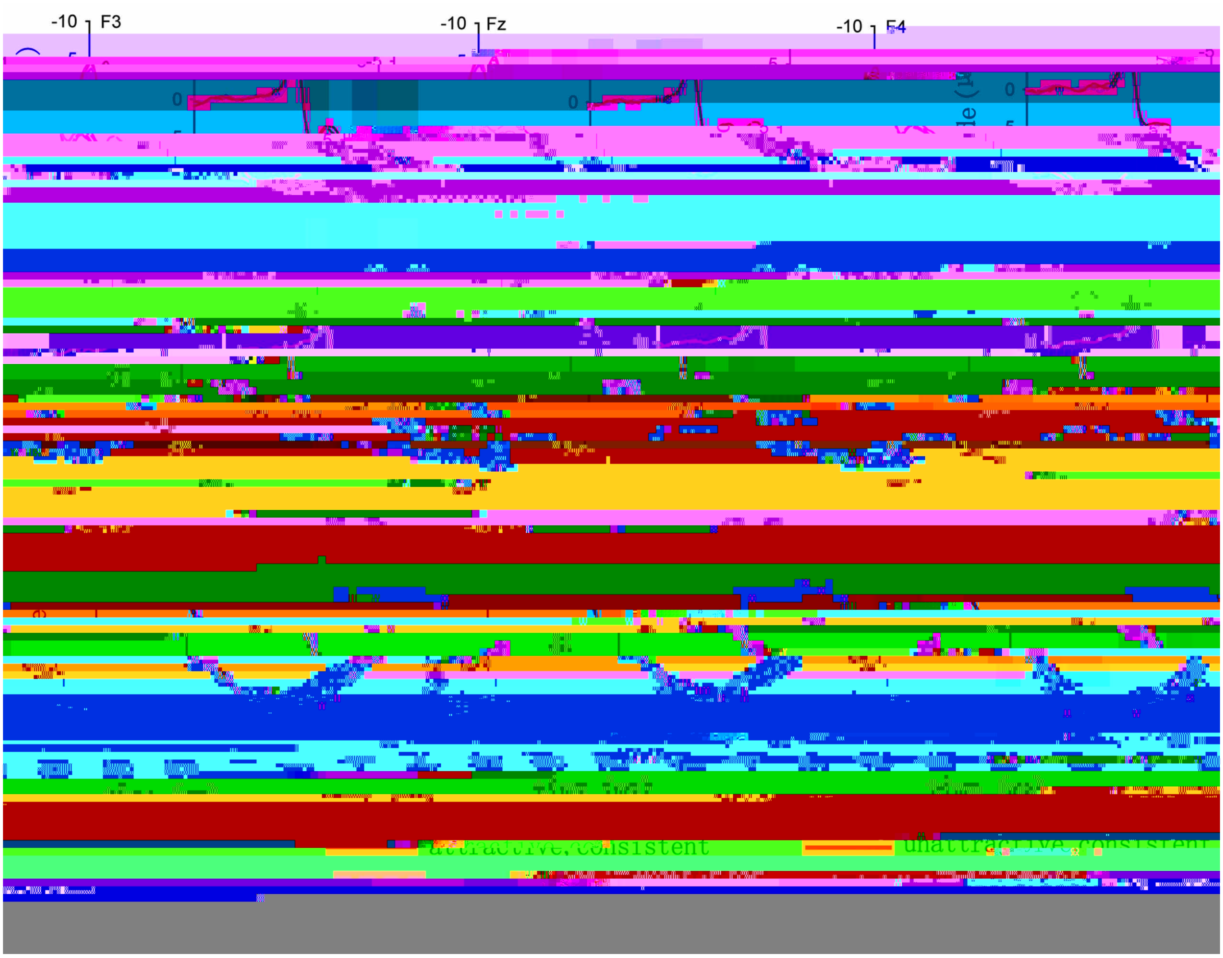

FIGURE 2 ERP

(PCA) on the ERP data (i.e., after preprocessing) in order to disentangle the overlapping and/or masked ERP components. PCA has a wide range of applications in ERP analysis, such as cleaning or filtering noises prior to data analysis, or being used in data exploration as a way to detect and summarize features of the dataset. In this study, we applied PCA on the cleaned ERP data to maximize the possibility that the PCA factors represent interpretable signals (i.e., brain activity due to experimental manipulations) as opposed to noise (i.e., artifacts or background EEG).

PCA is a common approach for decomposing an ERP dataset into its constituent factors by summarizing the relationship between variables (such as microvolt recordings at each time point in temporal PCA or at each electrode in spatial PCA; Dien and Frishkoff, 2005; Dien et al., 2005). This process consists of three main steps: (1) computation of the covariance matrix which captures the interrelationships between temporal/spatial variables; (2) extraction and retention of the PCA factors which extract linear combinations of variables (latent factors) to account for patterns of covariance in the ERP data with the fewest PCA factors; and (3) rotation to simple structure, which is used to restructure the allocation of variables to PCA factors to maximize the chance that each PCA factor reflects a single ERP component. These steps yield two matrices, which are useful in further analysis. The first one is a factor loading matrix, representing correlations between the variables and the factor scores (e.g., describing the time course of each of the PCA factors in temporal PCA). The second one is a factor score matrix that indexes

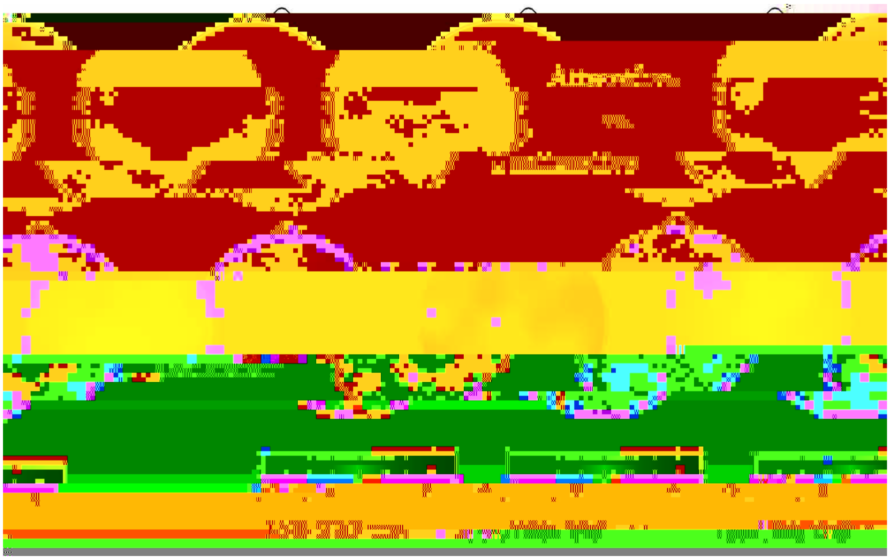

FIGURE 3 T a ERP

2009), with the most negative amplitudes in the 300–380 ms window and the most positive amplitudes in the 220–300 ms window

(Polich and Kok, 1995; Polich, 2007). The independence between