



Electrophysiological correlates of self-prioritization

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ABSTRACT

Personally relevant stimuli exert a powerful influence on social cognition. What is not yet fully understood, however, is how early in the processing stream self-relevance influences decisional operations. Here we used a shape-label matching task in conjunction with electroencephalography and computational modeling to explore this issue. A theoretically important pattern of results was observed. First, a standard self-prioritization effect emerged indicating that responses to self-related items were faster and more accurate than responses to other-related stimuli. Second, a hierarchical drift diffusion model analysis revealed that this effect was underpinned by the enhanced uptake of evidence from self-related stimuli. Third, self-other discrimination during matching trials was observed at both early posterior N1 and late centro-parietal P3 components. Fourth, whereas the N1 was associated with the rate of information accumulation during decisional processing, P3 activity was linked with the evidential requirements of response selection. These findings elucidate the electrophysiological correlates of self-prioritization.

1. Introduction

A common psychological finding is that self-relevant material is prioritized during information processing (Conway & Pleydell-Pearce, 2000; Humphreys & Sui, 2016; Markus & Nurius, 1986; Sui & Humphreys, 2015, 2017). For example, stimuli that have been referenced to, or associated with, the self (vs other people) are detected easily, judged rapidly, and remembered effectively (e.g., Bargh & Pratto, 1986; Constable et al., 2011; Golubickis et al., 2018; Keyes & Brady, 2010; Kuiper & Rogers, 1979; Schäfer et al., 2019; Shapiro et al., 1997; Sui et al., 2012; Symons & Johnson, 1997; Woźniak & Knoblich, 2019). These effects, moreover, emerge both for overlearned stimuli (e.g., one's face & name) and entirely arbitrary materials (e.g., shapes, colors, lines) that have temporarily been linked with the self (Humphreys & Sui, 2016; Sui & Humphreys, 2015, 2017). Reflecting a core component of social cognition, self-prioritization serves as a conduit through which information processing can be streamlined, adapted, and optimized.

In terms of its operational characteristics, self-bias during decision-making is believed to influence multiple stages of information processing (i.e., sensory processing, memory), primarily supported by the attentional enhancement of self-relevant (vs other-relevant) stimuli (Humphrey & Sui, 2016; Sui & Humphreys, 2015; Sui & Rotshtein, 2019). Specifically, through reciprocal connections between regions of the prefrontal (i.e., vMPFC) and temporal (i.e., pSTS) cortices, a combination of top-down and bottom-up processing operations increases the salience of personally relevant (vs other-relevant) material, thereby generating self-prioritization effects (Humphrey & Sui, 2016; Sui et al., 2013a, 2015). Corroborating this viewpoint, an extensive literature has demonstrated that self-relevance influences a range of attentional and memorial processes (e.g., Alexopoulos et al., 2012; Brédart et al., 2006;

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Cunningham et al., 2008; Devue & Brédart, 2008; Golubickis & Macrae, 2021; Li et al., 2022; Macrae et al., 2018; Moray, 1959; Rogers et al., 1977; Scheller & Sui, 2022a; Sui et al., 2006; Sun et al., 2016; Svensson et al., in press; Symons & Johnson, 1997; Tacikowski & Nowicka, 2010; Tong & Nakayama, 1999; Wójcik et al., 2018).

Notwithstanding these effects, of central interest are the decisional determinants of self-bias. In this respect, an emerging literature has identified critical boundary conditions (e.g., perceived relevance, prior knowledge) that moderate the emergence and magnitude of self-prioritization (Caughey et al., 2021; Falbén et al., 2021, 2019; Hu, Lan, Macrae, & Sui, 2020; Scheller & Sui, 2022b; Svensson et al., 2022; Woźniak & Knoblich, 2022). What is not yet fully understood, however, are the temporal characteristics of such stimulus-prioritization effects. Specifically, how early in the processing stream does self-relevance impact the decisional operations that give rise to self-bias? Accordingly, using a shape-label matching task (Sui et al., 2012) in combination with electroencephalography (EEG) and computation modeling (i.e., drift diffusion model analysis), we explored this matter in the current experiment. To our knowledge, this is the first study of its kind to combine behavioral and EEG data in a cognitive model of decision-making to probe the dynamics of self-prioritization.

Temporally sensitive event-related potentials (ERPs) are ideally suited to examine the time course of self-prioritization (Luck, 2005). As one would therefore expect, using ERPs to probe the temporal dynamics of self-bias has been a popular experimental approach. Inspection of the available literature, however, reveals mixed results. In work exploring the effects of self-relevance on ERPs associated with early processing (e.g., *P1*, *N1*, *P2*, *N2*), modulatory effects of self-association have typically been absent, thus challenging the contention that self-prioritization impacts initial stimulus-driven operations (Humphreys & Sui, 2016; Sui & Humphreys, 2015; Sui & Rotshtein, 2019).¹ In contrast, self-relevance has yielded reliable effects on ERP components linked with later decisional operations, most notably the *P3*. Occurring around 300–500 ms post stimulus onset, the *P3* is a positive deflection that has been associated with categorization and working memory operations (Nieuwenhuis et al., 2005; Polich, 2007; van Dinteren et al., 2014). Across an extensive literature, the amplitude of the *P3* has been shown to increase in response to an assortment of self-related targets, including (but not limited to) one's face, name, handwriting, car, hometown, and national flag (Berlad & Pratt, 1995; Chen et al., 2008; Fan et al., 2011; Folmer & Yingling, 1997; Gray et al., 2004; Ma & Han, 2010; Sui et al., 2009; Tacikowski & Nowicka, 2010). In contrast to material pertaining to other people, a recent study showed that self-related spatial cues improved task performance by decreasing the uncertainty of the location of upcoming targets (Liu et al., 2016). This was reflected by enhanced sensory processing (i.e., *N1* activity, Hillyard et al., 1998) and reduced uncertainty as indexed by the *P3* ERP component (Sutton et al., 1965). This effect has been taken to reflect the dynamic cognitive processing that is elicited by familiar self-relevant (vs other-relevant) stimuli.

Although the previous findings yield potential insights into the temporal dynamics of self-prioritization, a troublesome stimulus confound undermines the interpretation that self-relevance is the critical moderating factor (Sui et al., 2012; Woźniak & Knoblich, 2019). Problematically, not only are one's face and name (and national flag) personally relevant, so too they are highly familiar. As such, the reported ERP effects may derive from the familiarity rather than the self-relevance of the stimuli (i.e., information-processing prioritizes frequently encountered stimuli). To overcome this limitation, based on related behavioral research (Payne et al., 2017), Woźniak et al. (2018) conducted an investigation in which arbitrary stimuli (i.e., unfamiliar faces) were initially paired with person-related labels (i.e., you, friend, stranger). Next, in a sequential matching task, participants were presented with face-label stimulus pairs and required to report if each pairing matched (or mismatched) the previously learned associations (Sui et al., 2012). Crucially, absent a familiarity confound, self-prioritization was accompanied by modulation of the *P3*, thereby replicating work that has explored self-referential processing using personally familiar stimuli (Keyes et al., 2010; Miyakoshi et al., 2007; Perrin et al., 2005; Shi et al., 2011; Sui et al., 2006; Tacikowski & Nowicka, 2010; Zhou et al., 2010).

Given the dearth of research exploring the electrophysiological correlates of self-prioritization using arbitrary stimuli, here we also investigated this theoretically important topic, but with a couple of methodological and analytical modifications. First, rather than adopting a sequential matching task using shapes and unfamiliar faces (Woźniak et al., 2018), a standard matching paradigm was utilized in which shape-label pairings were presented simultaneously (Sui et al., 2012). This methodology is advantageous as it eliminates priming (i.e., expectancy-driven) effects during the task and has been the dominant paradigm in work exploring self-prioritization (Humphreys & Sui, 2016; Sui & Humphreys, 2015). Second, together with behavioral and electrophysiological analyses, computational modeling was also undertaken on the data (Bridwell et al., 2018). Specifically, a Drift Diffusion Model (DDM) analysis was conducted as previous research has successfully elucidated the cognitive processes underpinning self-prioritization through the application of this computational approach (e.g., Falbén et al., 2020; Golubickis et al., 2017, 2018, 2019, 2021; Hu et al., 2020; Svensson et al., 2022).

The DDM assumes that, during binary decision-making (e.g., do shape-label pairings match or mismatch previously learned associations?), noisy information is continually sampled until sufficient evidence has been accumulated to make a response (Ratcliff & Rouder, 1998; Ratcliff et al., 2016). The duration of the diffusion process is known as the decision time, and the process can be characterized by several latent parameters (Voss et al., 2013, 2015; White & Poldrack, 2014). Drift rate (v) estimates the speed of information acquisition, thus is interpreted as a measure of the quality of stimulus processing during decision-making (i.e., larger drift rate = faster information uptake). Boundary separation (a) estimates the distance between the two decision thresholds (e.g., matching

¹ A few studies have reported a decrease in the *N2* when processing one's own face compared to the faces of other people, an effect that is taken to reflect the overlearned (i.e., less surprising) status of one's appearance (Bola et al., 2021; Keyes et al., 2010; Sui et al., 2006, 2013b). Importantly, using arbitrary stimulus materials, Woźniak et al. (2018) demonstrated a comparable effect when an unfamiliar face denoted the self. In addition, modulation of the *N1* has been reported when words are encountered in a self-relevant linguistic context (Fields & Kuperberg, 2012) and self-faces as endogenous cues (Liu et al., 2016).

vs mismatching), hence indicates how much evidence is required before a response is made (i.e., larger values signal conservative responding). The starting point (z) defines the position between the decision thresholds at which evidence accumulation begins. If this is not centered between the thresholds ($z = 0.5$), this denotes a bias toward the response that is closer to the starting point. Finally, the duration non-decisional processes (e.g., stimulus encoding, response execution) is given by the parameter t_0 . Of particular significance to the current investigation is the drift rate (ν) parameter, as previous research has shown self-relevance to facilitate the speed of information accumulation (i.e., quality of visual processing) during shape-label matching tasks (Golubickis et al., 2017; Hu et al., 2020). We expected a similar effect to emerge here.

Importantly, application of a joint hierarchical Drift Diffusion Model (HDDM) makes it possible to explore the relationships between model parameters and neurophysiological measures, including EEG (i.e., computationally-informed EEG; see Bridwell et al., 2018; Kelly & O'Connell, 2015). The inclusion of such measures in the DDM is theoretically noteworthy on several grounds. First, it informs the neural correlates of the model parameters. Second, it integrates brain and behavioral data (Turner et al., 2016). At the neural level, replicating previous research, we expected self-relevance to modulate the P3 during decisional processing despite the adoption of arbitrary stimulus materials (Berland & Pratt, 1995; Gray et al., 2004; Tacikowski & Nowicka, 2010; Woźniak et al., 2018). Additionally, however, we also hypothesized that self-relevance would exert influence earlier in the processing stream (Woźniak & Knoblich, 2018), a prediction derived from popular accounts of self-function (Humphreys & Sui, 2016; Sui & Humphreys, 2015; Sui & Rotshtein, 2019). Elsewhere, salient stimuli — such as fearful faces, emotional images, and learned threats (Gupta et al., 2016; Keil et al., 2001; Linton & Levita, 2021; Olofsson et al., 2008; Schupp et al., 2003) — have been shown to modulate an early component of information processing, the N1. Occurring 150–200 ms post stimulus onset, this ERP component is thought to reflect the operation of a top-down mechanism that is critical for stimulus discrimination and subsequent processing (Luck, 2005). Given the acknowledged potency of self-relevance, we hypothesized that self-related (vs other-related) stimuli would similarly increase the amplitude of the N1 during shape-label matching (i.e., greater stimulus-driven processing of self-relevant [vs other-relevant] material).

To explore the link between the decision-making process and its electrophysiological correlates (Dmochowski & Norcia, 2015; Kelly & O'Connell, 2013; Manning et al., 2021), we integrated the behavioral and EEG data into a joint HDDM and tested the prediction that ERP activity associated with self-prioritization would be reflected in trial-by-trial changes in the rate of evidence accumulation (i.e., drift rate, ν) during decisional processing (Golubickis et al., 2017, 2020).

2. Method

2.1. Participants and design

Ten pairs of college friends ($M_{\text{age}} = 19.85 \pm 1.69$ years; 8 female) participated in the experiment. All participants had normal or corrected-to-normal vision. Informed consent was obtained prior to the commencement of the experiment and the protocol was reviewed and approved by the local ethics committee. The experiment had a 3 (Shape Association: self vs friend vs stranger) X 2 (Matching Condition: matching or mismatching) repeated measures design. Based on the large effect sizes reported in prior research exploring self-prioritization using shape-label matching tasks (Sui et al., 2012), a sample of 20 participants afforded 92 % power to detect an effect of $d = 1.0$ (PANGEA v0.2).

2.2. Stimulus materials and procedure

Participants were initially invited to the laboratory so the experiment could be explained. Individual testing sessions were then scheduled to take place over the following two weeks. On arriving at the laboratory, participants were informed they would be required to perform a shape-label matching task while their EEG was recorded. The shape-label matching task comprised two phases. First, shape-label associations were formed, such that participants learned that self, best friend (i.e., the person who initially accompanied them to the laboratory), and a stranger were represented by different geometric shapes (e.g., self = circle, friend = triangle, stranger = square). This learning phase took approximately-one minute to complete, and the stimuli were not displayed at this stage (Sui et al., 2012). Shape-label associations were counterbalanced across the sample. Second, participants then performed a matching task in which they judged whether a series of shape-label (e.g., self + triangle) pairs matched or mismatched the previously learned associations.

Each trial began with a central fixation cross ($0.8^\circ \times 0.8^\circ$) for 500 ms, followed by a shape-label pairing for 100 ms. The shape ($3.8^\circ \times 3.8^\circ$) was displayed above and the label ($3.1^\circ/3.6^\circ \times 1.6^\circ$ - You, Friend, Stranger) below the fixation cross on the screen. All stimuli were white and depicted against a grey background. Shape-label combinations were randomly presented across the trials (with an

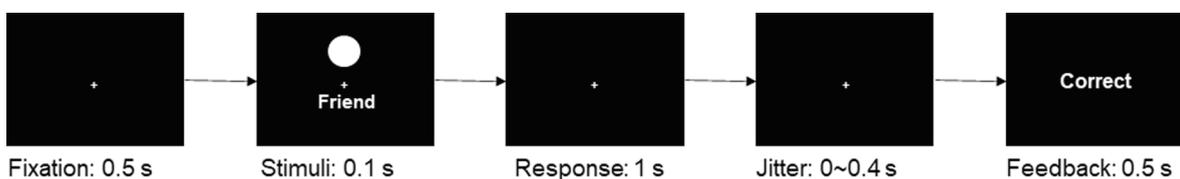


Fig. 1. Illustration of the procedure used in the matching task.

equal number of matching and mismatching trials) and participants were instructed to press the “M” and “N” keys, using the index and middle fingers of their right hand as quickly and accurately as possible, to provide a response. Response key mappings (i.e., matching or mismatching) were counterbalanced across participants. A response time window of 1.1 s was adopted and the intertrial interval varied between 0 and 400 ms. On a trial-by-trial basis, feedback was provided in the form of prompts (i.e., ‘correct’ or ‘incorrect’) that remained on the screen for 500 ms (see Fig. 1). Response time (RT) and accuracy were recorded. Preceded by 12 practice trials, the shape-label matching task comprised 16 blocks, with 60 trials per block. Thus, in total, each participant completed 960 experimental trials, with 160 trials in each condition (i.e., self-matching, friend-matching, stranger-matching, self-mismatching, friend-mismatching, stranger-mismatching) with short breaks between the blocks. Performance on mismatching trials was based on the shape that was presented in each pairing (e.g., self-mismatching trials corresponded to shape-label combinations in which the self-shape was paired with an incorrect label). The experiment was performed on a PC with a 15” CRT monitor. On completion of the task, participants were debriefed, thanked, and dismissed.

2.3. EEG recording and ERP processing

EEG data were recorded using a BioSemi Active Two system (BioSemi B.V.) at a sampling rate of 1,024 Hz from 128 scalp electrodes. The electrodes were fitted according to the 10–5 system (Oostenveld & Praamstra, 2001). Data were also recorded from the left and right mastoids for the purpose of referencing, and from below the left eye and at the outer canthi to monitor the vertical and horizontal electrooculogram (EOG), respectively. Analyses were conducted using BrainVision Analyzer 2.2.0 (Brain Products GmbH) with data from all EEG channels and the vertical EOG channel re-referenced to the mean voltage at the mastoids. The horizontal EOG was derived as a bipolar channel showing the difference between the left and right EOG electrodes.

For processing, the dataset evoked by each shape-label pairing was segmented into epochs which were later averaged to generate ERPs for the various experimental conditions. The dataset was subjected to a low-pass filter (zero-phase-shift Butterworth) with the cut-off frequency at 30 Hz (order 4). EEG data from trials containing correct manual responses were segmented into epochs from 200 ms before stimulus onset to 800 ms after stimulus onset (separately for each shape-label condition), with all voltage measured against the 200 ms pre-stimulus baseline period. Artifact rejection was carried out in two steps. First, recordings (across all channels) at time periods when the vertical or horizontal EOG channel showed activities stronger than a threshold of $\pm 60 \mu\text{V}$ were rejected due to blinks or eye movements. Second, excessively strong activities (over the $\pm 60 \mu\text{V}$ threshold), activities changing overly fast (over $50 \mu\text{V}/\text{ms}$), and persistently weak activities (weaker than $0.5 \mu\text{V}$ for at least 100 ms) were also removed as artefacts from the channels displaying concerns (i.e., individual channel mode). The remaining EEG segments were then averaged across trials for each experimental condition to generate the ERP waveforms.

ERP components (i.e., posterior N1, P3) were estimated as mean amplitudes at electrode locations and time windows determined using collapsed localizers (Luck & Gaspelin, 2017). This procedure collapsed over the experimental conditions to generate grand-average waveforms. These waveforms were then inspected to determine the locations and time windows for statistical analysis, typically locations and windows showing the strongest ERP activities. This procedure is generally condition-agnostic and greatly reduces the bias researchers might have when checking individual waveforms from all experimental conditions.

Given the typically narrow shape of the posterior N1 component, we used an analysis time window of 20 ms centered around the peak latency of the component. The collapsed localizer method determined the analysis to be over 147–167 ms at six bilateral temporal-parietal electrodes (P5, P6, TPP7h, TPP8h, P7, and P8). As P3 is a strong and long-lasting ERP component, a wide analysis window was used to cover its main activity period as seen in the condition-collapsed ERP waveforms. As such, the P3 component was identified from 340 to 500 ms at four parietal-occipital electrodes (Pz, PPO1h, PPO2h, and POz). As there were no hemispheric differences in the N1 component ($\text{BF}_{10} < 0.224$), neural activity was averaged across all electrodes in the cluster.

2.4. Drift diffusion modeling

Prior research exploring the computational underpinnings of self-prioritization has revealed that self-relevance facilitates the rate of information accumulation during decision-making (Golubickis et al., 2017, 2020; Hu et al., 2020; Svensson et al., 2022). Accordingly, to investigate the link between the decision-making process and its electrophysiological correlates (Dmochowski & Norcia, 2015; Kelly & O’Connell, 2013; Manning et al., 2021), we integrated behavioral and EEG data into a joint HDDM and tested the prediction that ERP activity associated with self-prioritization would be reflected in trial-by-trial changes in the rate of information uptake (i.e., drift rate, ν) during decisional processing (Cavanagh et al., 2011, Yau et al., 2021).

The HDDM analysis was conducted on the data (Vandekerckhove et al., 2011). HDDM is an open-source Python toolbox for the hierarchical Bayesian computation of DDM decisional components (Wiecki et al., 2013). The HDDM treats model parameters for individual participants as random samples constrained by group-level distributions (Vandekerckhove et al., 2011). Following previous research (Golubickis et al., 2017, 2020; Hu et al., 2020; Svensson et al., 2022), all models were response coded (i.e., upper threshold = matching response, lower threshold = mismatching response). For each estimated model, 3,000 Markov Chain Monte Carlo (MCMC) samples (1,500 burn-in) were simulated. Due to its computational efficiency and applicability when using hierarchical models, the Deviance Information Criterion (DIC) was adopted as a measure of fit for the model comparisons (Spiegelhalter et al., 1998). Lower DIC values indicate greater fit as they favor models with the least number of parameters and highest likelihood.

3. Results

3.1. Behavioral data

Responses faster than 200 ms were excluded from the analysis, eliminating <1 % of the data. A linear mixed model (LMM) analysis was used to examine the correct RTs. Analyses were conducted using JASP (Version 0.16.1, [JASP Team, 2022](#)). Shape Association and Matching Condition were treated as categorical fixed effects, and participants as a random effect ([Judd et al., 2012](#)). The analysis yielded main effects of Shape Association ($F = 149.99, p < .001$) and Matching Condition ($F = 956.45, p < .001$), and a significant Shape Association X Matching Condition ($F = 166.84, p < .001$) interaction.

To explore the interaction further, two Helmert contrasts were performed for each of the Matching Conditions ([Mattan et al., 2015](#); [Payne et al., 2017](#); [Schäfer et al., 2017](#) [Wozniak et al., 2018](#)). To test for the emergence of a self-prioritization effect, the first contrast compared self-related trials against the average of friend- and stranger-related trials. The second contrast compared friend-related against stranger-related trials (i.e., did a friend-bias emerge?). During matching trials, responses were faster to self-related compared to friend/stranger-related stimuli ($b = -0.41, SE = 0.02, z = -23.91, p < .001$; see [Fig. 2](#)). In addition, responses were faster to friend-related compared to stranger-related items ($b = -0.02, SE = 0.01, z = -7.04, p < .001$). During mismatching trials, no significant difference in RTs was observed between self-related compared to friend/stranger-related stimuli ($b = -0.01, SE = 0.02, z = -0.69, p = 1.00$). Responses were faster to stranger- compared to friend-related items ($b = 0.02, SE = 0.01, z = 4.80, p < .001$).

A binomial generalized LMM analysis was used to examine response accuracy. The analysis yielded a main effect of Shape Association ($\chi^2 = 50.26, p < .001$) and a significant Shape Association X Matching Condition ($\chi^2 = 116.11, p < .001$) interaction. As previously, Helmert contrasts were conducted to explore the interaction further. During matching trials, accuracy was higher for self-related compared to friend/stranger-related stimuli ($b = 0.39, SE = 0.04, z = 7.30, p < .001$; see [Fig. 2](#)). Additionally, responses were more accurate for friend- compared to stranger-related items ($b = 0.05, SE = 0.01, z = 5.33, p < .001$). During mismatching trials, accuracy did not differ significantly between self-related compared to friend/stranger-related stimuli ($b = -0.01, SE = 0.03, z = -0.32, p = 1.00$). Responses were more accurate for stranger-compared to friend-related items ($b = -0.03, SE = 0.01, z = 3.99, p < .001$).

3.2. ERP data

Self-prioritization was probed at the parietal N1 component and the centro-parietal P3 component. A LMM was conducted on the EEG data using JASP with Shape Association and Matching Condition treated as categorical fixed effects, and participants as a random effect.

N1 results. The analysis yielded only a significant Shape Association X Matching Condition interaction ($F = 13.42, p < .001$) (see Supplementary [Fig. 1](#)). To inspect the interaction further, Helmert contrasts were conducted. During matching trials, the first contrast indicated a greater N1 amplitude for self-related compared to friend/stranger-related stimuli ($b = -1.19, SE = 0.31, z = -3.92, p < .001$). The second contrast revealed no significant difference in N1 amplitude between friend- and stranger-related items ($b = -0.39, SE = 0.35, z = -1.10, p = .274$, see [Fig. 3](#)). During mismatching trials, the N1 amplitude was greater for friend/stranger-related compared to self-related stimuli ($b = -1.01, SE = 0.31, z = -3.11, p < .001$). No significant difference in the N1 amplitude was observed between friend- and stranger-related stimuli ($b = 0.04, SE = 0.35, z = 0.11, p = .916$, see [Fig. 4](#)). Finally, the N1 amplitude was greater for self-matching stimuli compared to friend-/stranger-related mismatching stimuli in which the self-label appeared ($b = -0.62, SE = 0.31, z = -2.02, p = .044$); but this was not the case for either friend-matching stimuli compared to self-/stranger-related mismatching stimuli

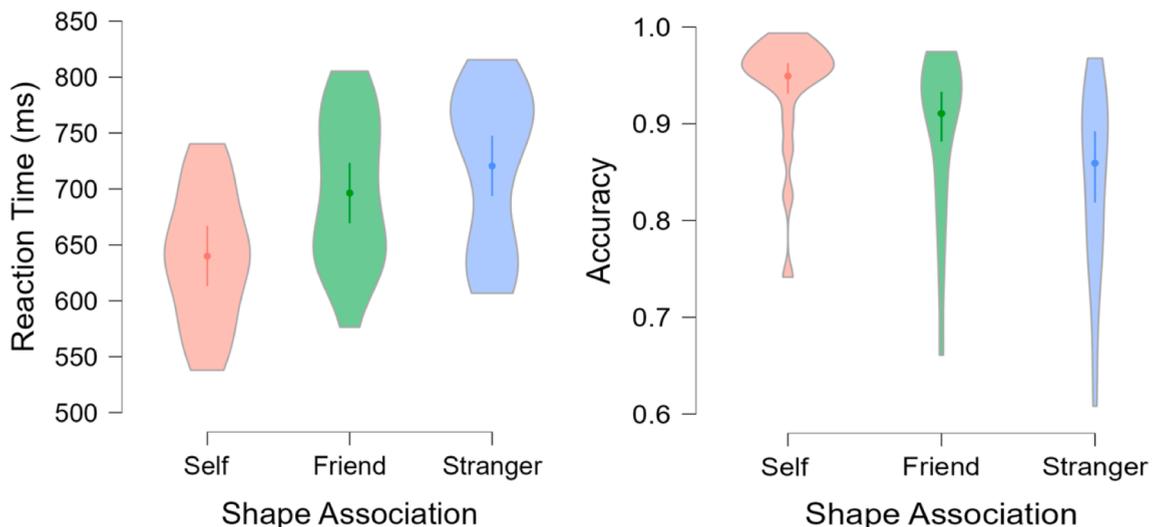


Fig. 2. RT and accuracy as a function of Shape Association during matching trials.

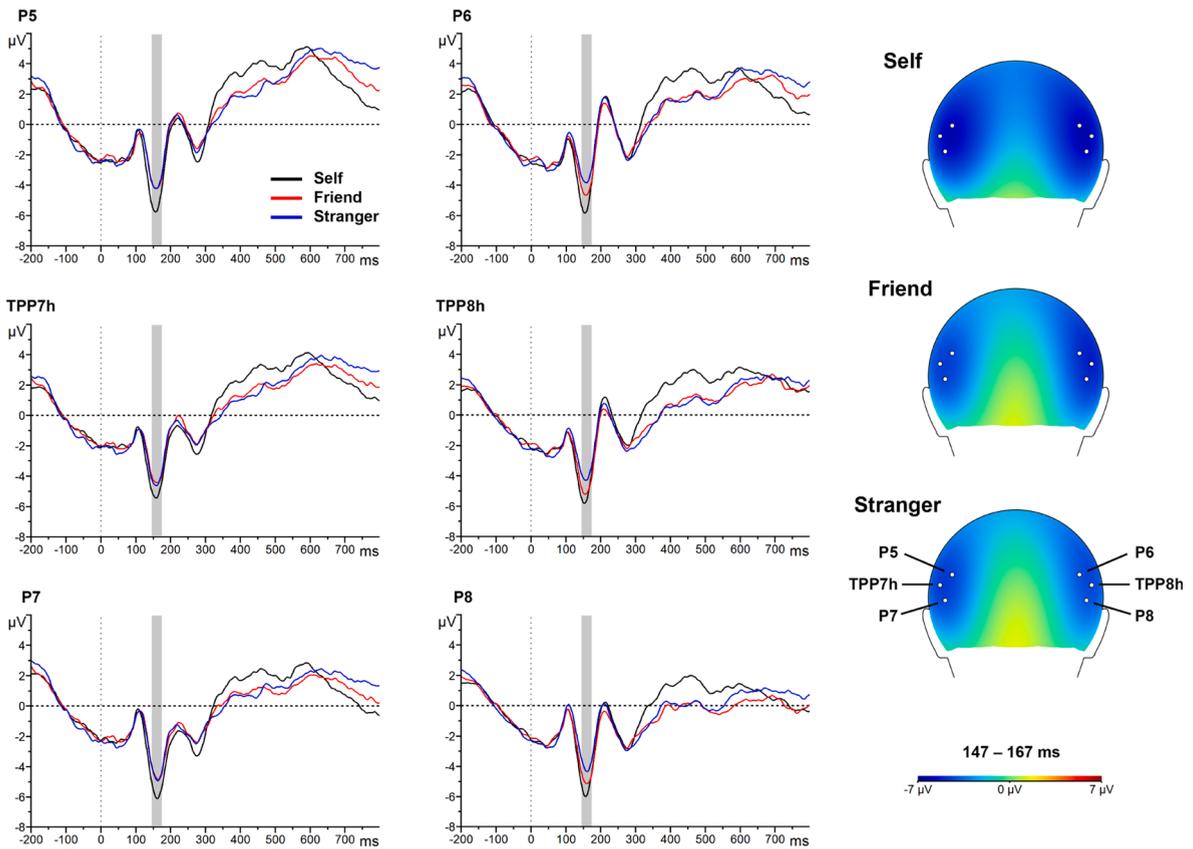


Fig. 3. The left and middle panels: averaged wave forms of the N1 component at 147–167 ms as a function of Shape Association during matching trials from the posterior regions (p5/6, TPP7h/8h, p7/p8). The right panel: the topography of N1 and mean amplitude (uV) of the component as a function of Shape Association during matching trials.

(with the friend-label) ($b = -0.11, SE = 0.31, z = -0.36, p = .719$) or stranger matching stimuli compared to self-/friend-related mismatching stimuli (with the stranger-label) ($b = 0.26, SE = 0.31, z = 0.84, p = .400$).

P3 results. The analysis revealed main effects of Shape Association ($F = 10.05, p < .001$) and Matching Condition ($F = 35.49, p < .001$), and a significant Shape Association X Matching Condition ($F = 7.41, p < .001$) interaction (see Supplementary Fig. 2). As before, Helmert contrasts were conducted to examine the interaction further. During matching trials, the first contrast indicated a greater P3 amplitude for self-related compared to friend/stranger-related stimuli ($b = 1.92, SE = 0.33, z = 5.83, p < .001$). The second contrast revealed no significant difference in P3 amplitude between friend- and stranger-related items ($b = 0.32, SE = 0.38, z = 0.85, p = .398$, see Fig. 5). During mismatching trials, the P3 amplitude did not differ significantly between self- and friend/stranger-related stimuli ($b = 0.16, SE = 0.33, z = 0.48, p = .634$), nor between friend-related and stranger-related stimuli ($b = -0.06, SE = 0.38, z = -0.15, p = .872$, see Fig. 6).

3.3. Drift diffusion modeling and Trial-By-Trial EEG correlates

Several models were estimated for comparison to identify trial-by-trial correlations between ERP components and DDM parameters using the HDDMRegression function. Previously, a model that allowed drift rate (v) to vary as a function of Shape Association and Matching Condition, with a single estimate of the starting point (z), boundary separation (a) and non-decision time (t_0), was reported to be best the fitting in shape-label matching tasks (i.e., default model; Golubickis et al., 2017, 2020; Svensson et al., 2022). As such, all models included this parameterization together with inter-trial variability for drift rate (sv), non-decision time (st), and starting point (sz). Importantly, the models also allowed trial-by-trial variation of neural activity (i.e., N1 & P3) to modulate decisional parameters. First, compared to the P3 (DIC = -10433), allowing drift rate (v) to vary parametrically with the amplitude of the N1 yielded a better model fit (DIC = -10449), thereby suggesting that the N1 is more strongly associated with speed of information uptake parameter. Second, compared to the N1 (DIC = -9854), allowing boundary separation (a) to vary with the amplitude of the P3 improved model fit (DIC = -10071). This suggests that the P3 is associated with decisional processing. Based on these findings, a model that regressed the N1 onto v and the P3 onto a was estimated. This model was best fitting (DIC = -10591), even in comparison with more complex models that allowed drift rate and boundary separation to vary parametrically with both ERP components (DIC = -9301).

Analysis of the posterior distributions of the best fitting model revealed that, during matching trials, there was extremely strong

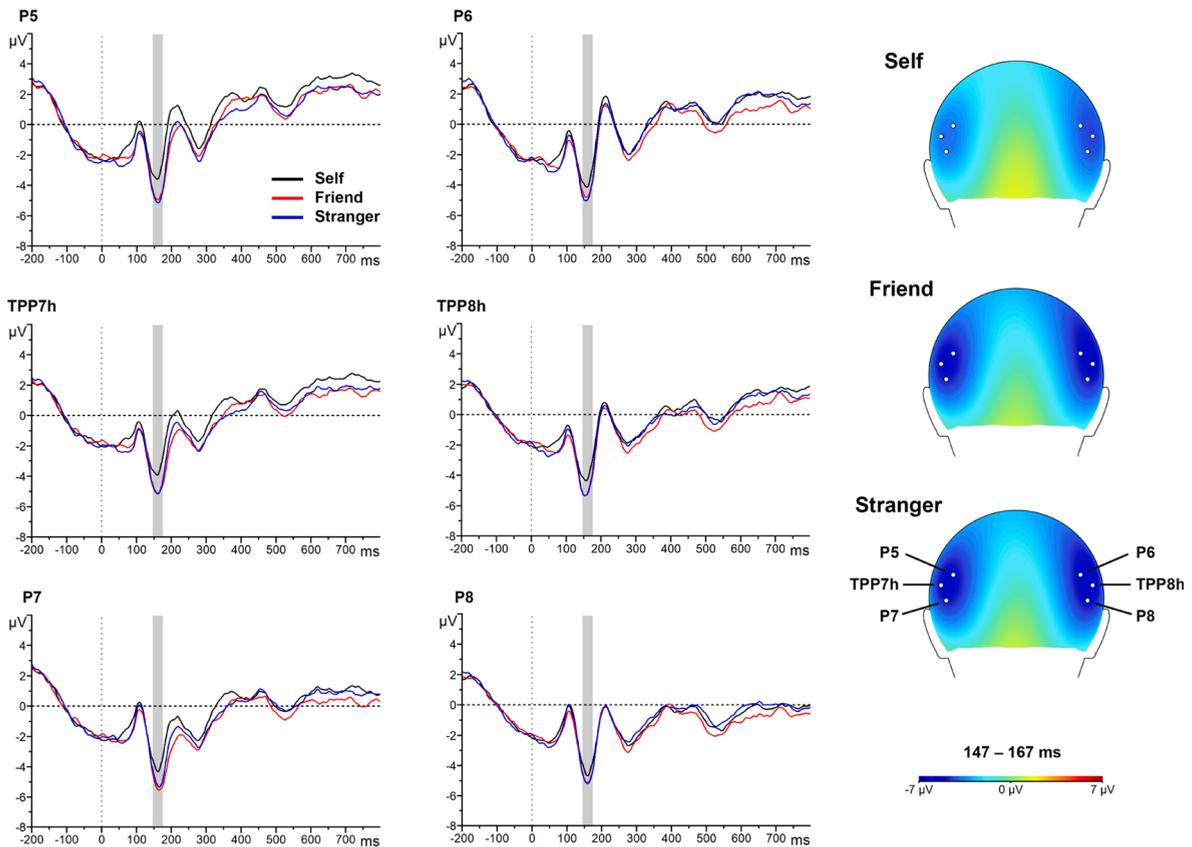


Fig. 4. The left and middle panels: averaged wave forms of the N1 component at 147–167 ms as a function of Shape Association during mismatching trials from the posterior regions (p5/6, TPP7h/8h, p7/p8). The right panel: the topography of N1 and mean amplitude (uV) of the component as a function of Shape Association during mismatching trials.

evidence that information uptake (i.e., drift rate) was faster for self-related compared to friend-related stimuli ($p_{\text{Bayes}}[\text{self} > \text{friend}] < 0.001$, $\text{BF} > 1000$) and friend-related compared to stranger-related items ($p_{\text{Bayes}}[\text{friend} > \text{stranger}] < 0.001$, $\text{BF} > 1000$; see Fig. 7). During mismatching trials, there was very strong evidence that information sampling was faster for self-related compared to friend-related items ($p_{\text{Bayes}}[\text{self} > \text{friend}] = 0.023$, $\text{BF} = 43$), but slower for self-related compared to stranger-related stimuli ($p_{\text{Bayes}}[\text{stranger} > \text{self}] = 0.001$, $\text{BF} = 769$; see Fig. 7). In addition, comparing the starting point value (z) with no bias ($z = 0.50$) yielded extremely strong evidence of a response bias in favor of matching (vs mismatching) judgments ($p_{\text{Bayes}}[\text{bias} > 0.50] < 0.001$, $\text{BF} > 1000$). For the trial-by-trial EEG regressors, there was strong evidence for an increase in the rate of information uptake as the N1 amplitude spiked more negatively ($p_{\text{Bayes}}[\text{drift rate} \sim \text{N1}] = 0.073$, $\text{BF} = 14$), and extremely strong evidence for a decrease of boundary separation as the P3 amplitude spiked more positively ($p_{\text{Bayes}}[\text{boundary separation} \sim \text{P3}] < 0.001$, $\text{BF} > 1000$; see Fig. 7).

4. Discussion

Using ERPs in combination with hierarchical drift diffusion modeling, here we sought to explicate the electrophysiological correlates of self-prioritization during a shape-label matching task. Four results were observed. First, reflecting the emergence of a typical self-prioritization effect, responses were faster and more accurate to self-related items compared to stimuli associated with other persons. Second, a joint HDDM analysis indicated that this prioritization effect was underpinned by facilitated stimulus processing. Specifically, evidence was accumulated most rapidly from self-related (vs friend- or stranger-related) shape-label pairings. Third, at the neural level, self-other discrimination during matching trials was observed at both early posterior N1 (150–200 ms) and late centroparietal P3 (300–500 ms) ERPs. During mismatching trials, however, the effect on N1 was reversed. Fourth, whereas the N1 was related to the rate of information uptake (i.e., drift rate, ν) during decisional processing, P3 activity was linked with the evidential requirements of response selection (i.e., boundary separation, a). Collectively, these findings inform understanding of the origin and time course of self-prioritization during decisional processing.

A key assumption of recent theoretical accounts of self-function is that personally meaningful material dynamically influences information processing (Sui & Humphreys, 2015; Sui, 2016), including early attentional operations (Humphreys & Sui, 2016; Sui & Rotstein, 2019). That is, self-reference enhances the social salience of stimuli through the activation of the self-concept, which in turn modulates cognitive processes, resulting in optimal task performance (Sui & Humphreys, 2015). In the context of the matching task,

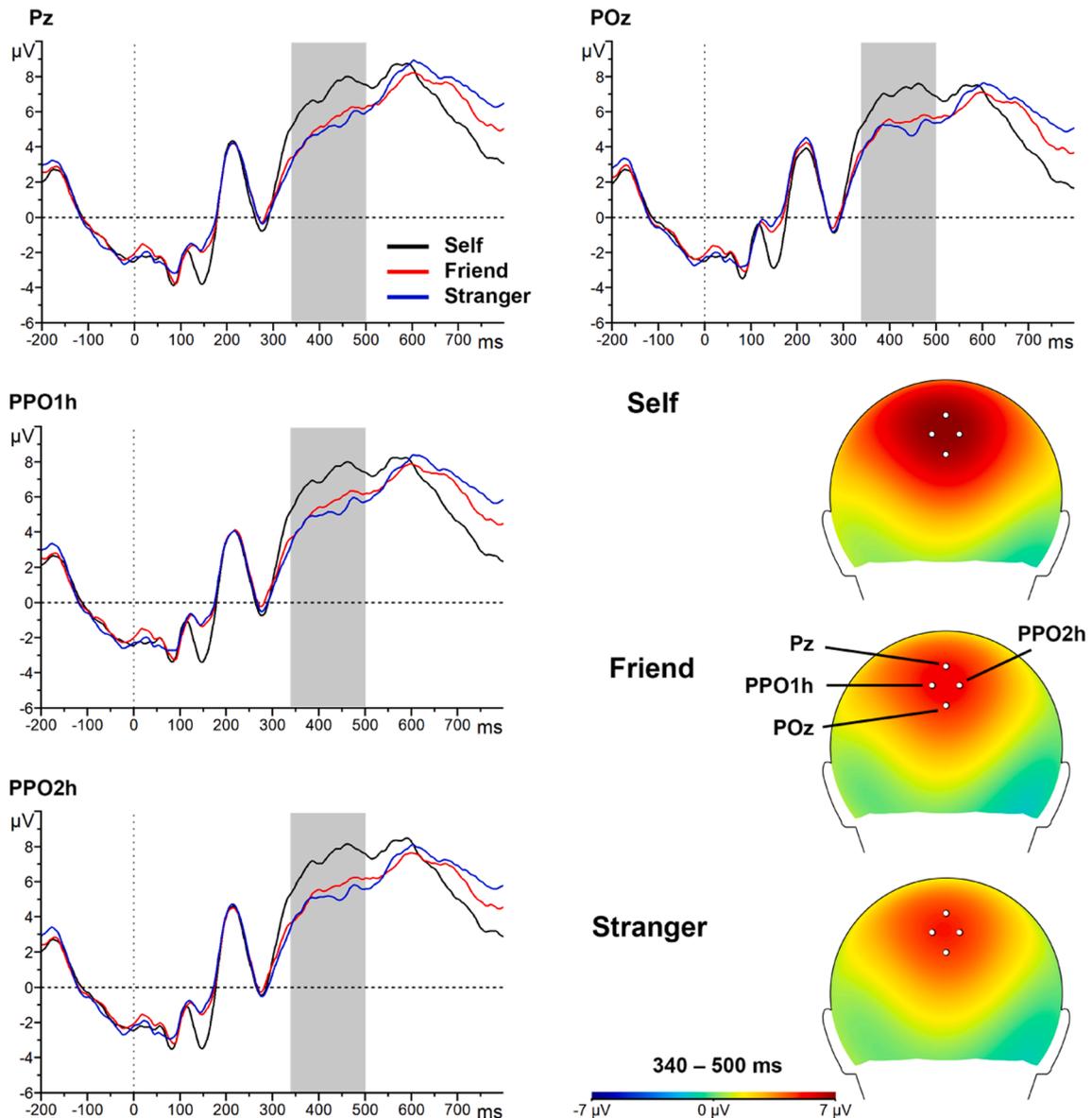


Fig. 5. The left and top-right panels: averaged wave forms of the P3 component at 340–500 ms as a function of Shape Association during matching trials from the posterior central regions (Pz, POz, PPO1h/2h). The bottom right panel: the topography of the P3 and mean amplitude (μV) of the component as a function of Shape Association during matching trials.

the label triggers self-activation, which tunes attention to personally relevant external input (e.g., I am a square). It is the rapid integration of the shape and label during decision-making that is believed to generate the self-prioritization effect. Evidence supporting this viewpoint, however, is limited (Dalmaso et al., 2019; Golubickis & Macrae, 2021; Li et al., 2022; Macrae et al., 2018; Orellana-Corrales et al., 2020, 2021; Svensson et al., 2022). Although both behavioral and electrophysiological investigations have demonstrated such effects, these studies have ordinarily examined cognitive processes in isolation (Berland & Pratt, 1995; Chen et al., 2008; Fan et al., 2011; Folmer & Yingling, 1997; Gray et al., 2004; Liu et al., 2016; Ma & Han, 2010; Tacikowski & Nowicka, 2010). As a result, it remains unclear how the reported effects derive from the integrative process of self-referencing. Crucially, using a shape-label matching task combined with integrated hierarchical Bayesian modeling and ERPs, here we furnished evidence for the modulatory effects of self-relevance during decisional processing.

The adoption of an integrated hierarchical Bayesian modeling approach yielded valuable insights into the processes underpinning self-prioritization and their neural implementation (Bridwell et al., 2018; Kelly & O'Connell, 2015; Turner et al., 2016). Replicating prior work, self-prioritization was driven by the increased rate of evidence accumulation (i.e., drift rate [v] parameter) during decisional processing, a finding that underscores the importance that stimulus-driven operations (i.e., integration of simultaneously presented signals) play in the emergence of self-bias (Golubickis et al., 2017, 2020; Hu et al., 2020; Svensson et al., 2022). Further

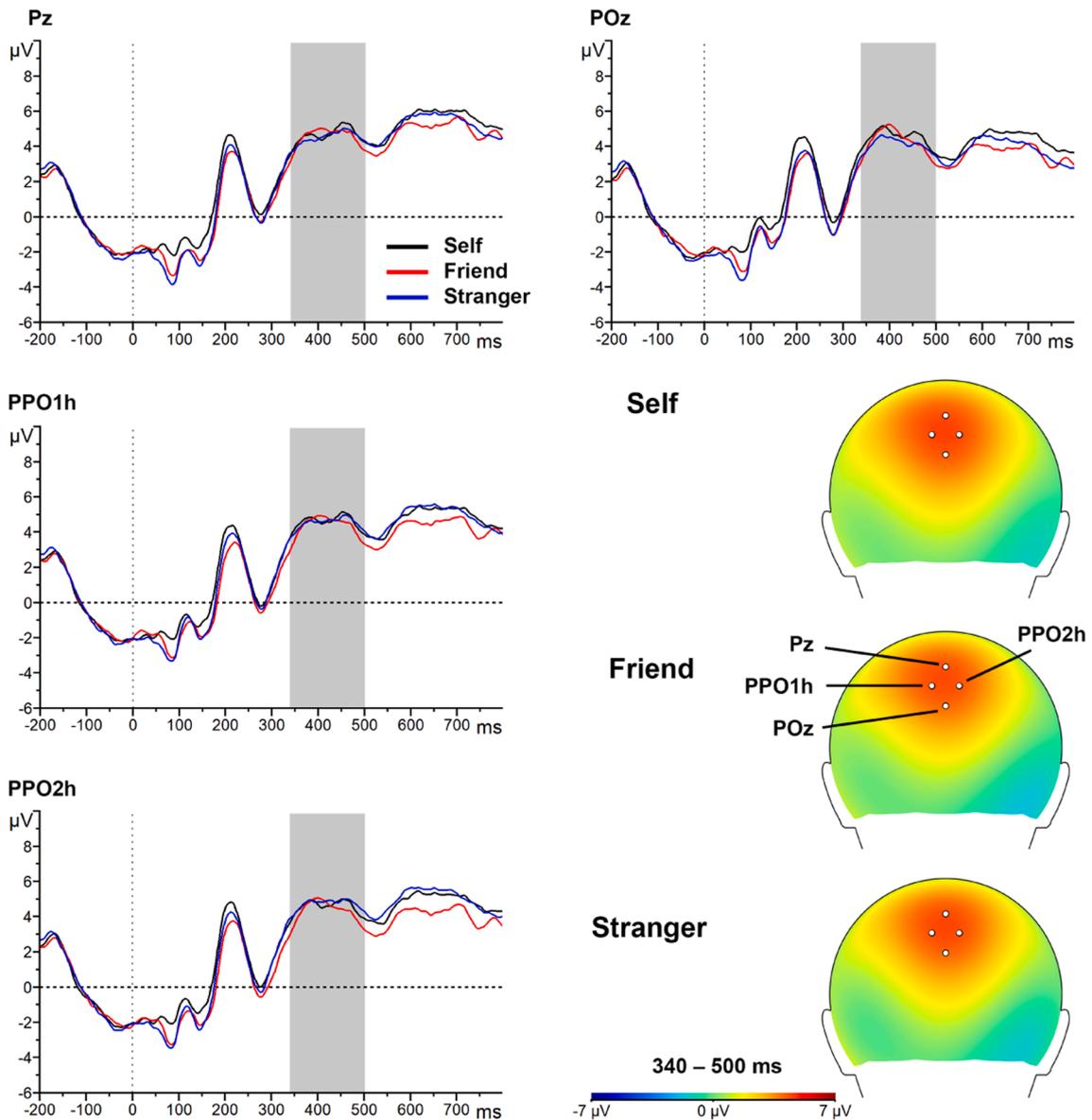


Fig. 6. The left and top-right panels: averaged wave forms of the P3 component at 340–500 ms as a function of Shape Association during mismatching trials from the posterior central regions (Pz, POz, PPO1h/2h). The bottom right panels: the topography of the P3 and mean amplitude (μV) of the component as a function of Shape Association during mismatching trials.

endorsing this viewpoint, N1 activity was associated with the drift rate parameter, suggesting that this ERP component is linked with the rate of evidence accumulation (i.e., early shape/label integration boosts the continuous gathering of decisional evidence). Additionally, self-relevance also impacted operations later in the processing stream — notably the P3 — an effect that was related to the boundary separation (a) parameter in the diffusion model (i.e., how much evidence was required to select a response?). As reduced boundary separation reflects greater decisional assurance (Ratcliff et al., 2016), this suggests that P3 activity indexed response confidence when making self-relevant (vs other-relevant) judgments (Boldt & Yeung, 2015; Curran, 2004; Liu et al., 2016; Yau et al., 2021). Collectively, these findings underscore the utility of computational approaches to social cognition (Hackel & Amodio, 2018; Lockwood & Klein-Flügge, 2020). Through advanced modeling, here we pinpointed, at both cognitive and neural levels, the sensory and decisional processes that underpin self-prioritization.

Based on an extensive literature, the N1 is believed to index an early discrimination process (Fedota et al., 2012; Hopf et al., 2002; Luck, 2005; Vogel & Luck, 2000). Specifically, through the differential engagement of top-down attention, gain control mechanisms serve to enhance stimulus discrimination via the amplification of sensory processing (Hillyard et al., 1998). In the current study, during the simultaneous presentation of the stimuli (cf. Woźniak et al., 2018), greater N1 activity could be triggered by initial perception of the shape, the label, or the stimuli in combination. Analysis of the mismatching trials was informative on this matter. Specifically, the

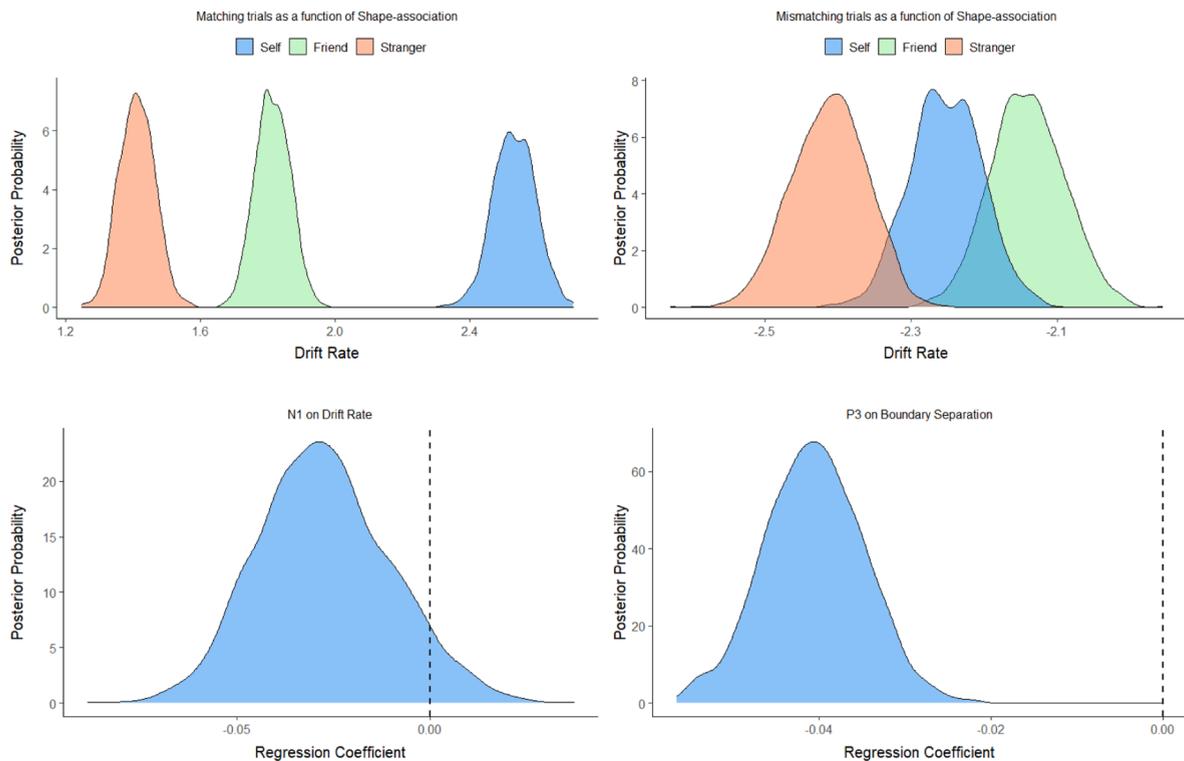


Fig. 7. Mean posterior parameter distributions of drift rate (v) as a function of Shape Association and Trial Type and mean posterior regression coefficient distributions of N1 on drift rate (v) and P3 on boundary separation (a).

N1 was more sensitive to friend/stranger-mismatching trials, in which the label “you” appeared, compared to self-mismatching trials in which the label was absent. More importantly, the simultaneous presence of a self-associated shape and label (i.e., self-matching stimuli) elicited the greater N1 amplitude when compared to the presence of the self-label (i.e., friend-/stranger-related mismatching stimuli). In contrast, no such effect was observed when comparing friend-matching stimuli to the friend-label (i.e., self-/stranger-related mismatching stimuli) or when comparing stranger-matching stimuli to the stranger-label (i.e., self-/friend-related mismatching stimuli). These results indicate that the early ERP activity, and therefore the evidence accumulation process, might be driven by the simultaneous presence of the self-shape-label pairings. These findings are consistent with the contention that arbitrary self-relevant stimuli together with the label “you” modulate early attentional processes as indexed by increased neural activity in the pSTS (Sui et al., 2013). Here, we propose that early detection of the label “you” is integrated with the shape through the gradual accumulation of decisional evidence, thereby boosting stimulus-based processing efficiency during self-matching and friend/stranger-mismatching trials.

Interestingly, other potent classes of stimuli have also been demonstrated to modulate N1 activity (Gupta et al., 2016; Keil et al., 2001; Olofsson et al., 2008; Schupp et al., 2003). Since overlearned (i.e., highly familiar) stimulus materials have typically been used to explore self-prioritization, some of these effects can be traced to the familiarity of the items under investigation (Berland & Pratt, 1995; Chen et al., 2008; Fan et al., 2011; Folmer & Yingling, 1997; Gray et al., 2004; Liu et al., 2016; Ma & Han, 2010; Tacikowski & Nowicka, 2010). Here using a shape-label matching task to overcome this limitation (see also Woźniak et al., 2018), we provided evidence for the modulatory effects of self-relevance (i.e., shape-label integration) early in the processing stream. Although self shape-label integration yielded a stronger effect compared to the familiar label alone, it is possible that the presence of the familiar label may be a key driver of such effect. To investigate this possibility, future research should examine whether the reported effects would disappear in the absence of familiar labels. As such, using the arbitrary items of interest instead of familiar labels (e.g., shape-color combination, see Lee et al., 2021; Woźniak & Knoblich, 2019), researchers should explore whether a comparable effect emerges when otherwise meaningless stimuli are rendered self-relevant (vs other-relevant) through prior association (Sui et al., 2012). In so doing, such work would corroborate the assumption that personally meaningful stimuli benefit from augmented attentional processing during the early stages of decision-making (Humphreys & Sui, 2016; Sui & Humphreys, 2015).

Replicating previous research on the topic, as indexed by increased P3 activity, self-prioritization was also observed later in the processing stream (Keyes et al., 2010; Miyakoshi et al., 2007; Perrin et al., 2005; Shi et al., 2011; Sui et al., 2006; Tacikowski & Nowicka, 2010; Woźniak et al., 2018; Zhou et al., 2010). Although the precise functional significance of the P3 remains a matter of continued debate, one prominent account suggests it comprises a neural decision variable (Polich, 2007; Twomey et al., 2015). In this regard, the elevated P3 activity that accompanied self-prioritization could potentially reflect a range of decisional operations, including the increased accessibility of shape-label relations in working memory, the judgmental significance of motivationally

relevant material, and the confidence associated with specific responses (Nieuwenhuis et al., 2005; Polich & Kok, 1995; Urai & Pfeffer, 2014; Verleger et al., 2015).

The current experiment is not without limitation. First and foremost, only a shape-label matching task was used to probe the time course of self-prioritization. Although this paradigm has arguably become the gold standard for exploring self-bias during decision-making (Humphreys & Sui, 2016; Sui & Humphreys, 2015), other approaches are available. For example, ownership tasks in which participants must decide to whom (e.g., self or friend) arbitrary objects belong also reliably generate self-prioritization effects (e.g., Constable et al., 2011; 2019; Golubickis et al., 2018, 2021). Interestingly, however, these effects appear grounded in response-selection biases rather than the efficiency of stimulus processing (Constable et al., 2019; Golubickis et al., 2018; but see Falbén et al., 2020). For example, Constable et al. (2019) demonstrated that when judging which of two objects initially appeared on the computer screen (i.e., a mug owned by self or a mug owned by the experimenter), participants were biased toward reporting that self-owned objects were presented first (i.e., prior-entry effect). This self-bias was eliminated, however, when the requested judgment tapped a stimulus dimension unrelated to identification or ownership (i.e., did the mug appear to the left or right of fixation?), thereby implying that a criterion shift during response selection triggered self-prioritization (Caughey et al., 2021; Golubickis et al., 2018; Scheller & Sui, 2022b). Of theoretical interest, therefore, is whether the ERP and modeling results observed in the current experiment would generalize beyond shape-label matching tasks. Future research should address this matter.

Consideration should also be given to prioritization effects that emerge for persons other than the self. Recent work has demonstrated that stimulus enhancement is highly task dependent with participants prioritizing whichever material is most salient/goal-relevant in the immediate task context (Falbén et al., 2020; Scheller & Sui, 2022b; Svensson et al., 2022; Woźniak & Knoblich, 2022). For example, whether in an expectancy-confirmatory or expectancy-violating setting, prioritization effects emerge for whichever stimuli (i.e., self-related or friend-related) are encountered most frequently (Falbén et al., 2020; Svensson et al., 2022). That is, when stimuli pertaining to a friend predominate, participants prioritize friend-related compared to self-related material. If prioritization effects derive from the workings of domain general operations (cf. Humphreys & Sui, 2016; Sui & Humphreys, 2015), then one would expect biases toward friend-related stimuli to be accompanied by the EEG and modeling effects observed here. Specifically, grounded in both sensory and decisional processing, friend-prioritization should be linked with N1 and P3 activity during decision-making.

In sum, integrating behavioral and EEG data into a joint HDDM, here we clarified both the origin and time course of self-prioritization during a shape-label matching task (Sui et al., 2012). Compared to stimuli related to a friend or stranger, self-association modulated ERP components allied with early (i.e., N1) and later decisional (i.e., P3) processing. In addition, these components correlated with the rate of information accumulation (i.e., drift rate) and evidential requirements of response selection (i.e., boundary separation), respectively. Extending influential accounts of self-function (Humphreys & Sui, 2016; Sui & Humphreys, 2015, 2017), these findings inform understanding of exactly how and when self-relevance biases decisional processing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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