Good Me Bad Me:

Prioritization of the Good-Self During Perceptual Decision-Making

Chuan-Peng Hu *

Department of Psychology, Tsinghua University, 100084 Beijing, China,

German Resilience Center, 55131 Mainz, Germany,

Yuxuan Lan

School of Life Science, Tsinghua University, 10084 Beijing, China

C. Neil Macrae

School of Psychology, University of Aberdeen, Aberdeen, Scotland

Jie Sui

Department of Psychology, University of Aberdeen, Aberdeen, Scotland

Authors Note

This work was supported by NSFC 31371017 to J.S. We embrace the values of openness and transparency in science (www.researchtransparency.org/). We report how we determined the sample size, data exclusions (if any), manipulations, and all measures in the study, and refer to the project documentation in the OSF and GitHub(https://osf.io/4zvkm/, https://github.com/hcp4715/moralSelf_ddm). All raw data and the scripts for data analyses are also available (see the additional materials in the OSF and GitHub).

*** Correspondence**: C-P. Hu, hcp4715@gmail.com

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Abstract

People display systematic priorities to self-related stimuli. As the self is not a unified entity however, it remains unclear which aspects of the self are crucial to producing this stimulus prioritization. To explore this issue, we manipulated the valence of the self-concept (good me vs. bad me) — a core identity-based facet of the self — using a standard shape-label association task in which participants initially learned the associations (e.g., circle/good-self, triangle/good-other, diamond/bad-self, square/bad-other), after which they completed shape-label matching and shape-categorization tasks, such that attention was directed to different aspects of the stimuli (i.e., self-relevance and valence). The results revealed that responses were more efficient to the good-self shape (vs. other shapes), regardless of the task that was undertaken. A hierarchical drift diffusion model (HDDM) analysis indicated that this good-self prioritization effect was underpinned by differences in the rate of information uptake. These findings demonstrate that activation of the good-self representation exclusively facilitates perceptual decision-making, thereby furthering understanding of the self-prioritization effect.

Keywords: self-relevance, good-self, drift diffusion model, perceptual decision-making

The greatest magnifying glasses in the world are a man's own eyes when they look upon his own person. (Alexander Pope, 1688-1744)

To optimize social-cognitive functioning, people need to prioritize processing so that stimuli relevant to their goals are selected for action. As such, a crucial stimulus property is self-relevance. People prioritize information related to themselves compared to others, such as the cocktail party effect (Moray, 1959) and the self-referential advantage in memory (Rogers, Kuiper, & Kirker, 1977). Despite long-standing interest in these self-prioritization effects (Greenwald, 1980), however, questions remain regarding the conditions under which self-bias arises. Complicating this issue is the inherently multifaceted character of the self-concept (C. Hu et al., 2016). A dominant explanation for self-prioritization effects is that they reflect the intrinsic positive valence of self-related stimuli. Supporting evidence comes from the elimination of self-bias when people are required to evaluate unfavorable personality traits in relation to themselves (Ma & Han, 2010) and when their mood is low (Sui, Ohrling, & Humphreys, 2016). Relatedly, researchers have reported that the attentional benefits of self-relevance are greater when targets are probed by positive identity-based (versus irrelevant) cues (Macrae, Visokomogilski, Golubickis, & Sahraie, 2018). Notwithstanding these consistent findings, there is little direct evidence of whether the self-prioritization effect results from a core identity-centred aspect of the self (e.g., good me); that is, whether the positive (vs. negative) valence of the self-concept is crucial to the emergence of self-bias.

We set out to address this issue using a standard shape-label association task that has been used to explore self-prioritization during perceptual decision-making (Sui, Rotshtein, & Humphreys, 2013). Participants first associated good and bad aspects of the self (and stranger) with different geometric shapes, then judged whether a subsequent series of shape-label pairings matched or mismatched the previously learned associations (Sui, He, & Humphreys, 2012). Previous studies have consistently shown that people reliably favor self-related shapes compared to shapes associated with others (e.g., Sui et al, 2012). We therefore considered whether this self-prioritization effect in perceptual matching is modulated by valence, such that self-bias is sensitive to the identity-based aspect of the self (i.e., good me) with which stimuli are associated. In addition, we had participants carry out a shape-categorization task in which they were required to classify briefly presented stimuli according to valence or self-relevance. This task probed stimulus prioritization in a task context in which the self-relevance of the material was orthogonal to the dimension of interest.

Work in social psychology has repeatedly demonstrated the effects of valence on self-referential processing and self-evaluation (i.e., good-self vs. bad-self; Greenwald, 1980; Pronin, 2008; Sedikides & Strube, 1997). For example, researchers have reported that participants spend more time reading positive than negative information about themselves (Baumeister & Cairns, 1992), unfavourable self-related events are more likely to be forgotten than their favourable counterparts (X. Hu, Bergström, Bodenhausen, & Rosenfeld, 2015), and positive outcomes are more likely to be escribed to the self than others, with negative outcomes exhibiting the opposite attributional pattern (Pronin, 2008). A long-standing interpretation of these effects is that a basic self-enhancement motive facilitates the processing of positive (vs. negative) information, thereby protecting the self-concept from challenge and enabling people to maintain an unrealistically positive conception of themselves (Sedikides & Strube, 1997). From these findings, we predict that self-prioritization will be greater when geometric shapes are paired with the good- compared to bad self, regardless of the task that is undertaken on the stimuli. To elucidate the processes underpinning task performance, data will be submitted to a hierarchical drift diffusion model (HDDM) analysis (Wiecki, Sofer, & Frank, 2013). Based on previous research, we expect self-prioritization to be underpinned by a stimulus bias (i.e., rate of evidence accumulation) during decisional processing (Golubickis et al., 2017).

Method

The current experiment was based on a pre-registered pilot study (see Supplementary Materials 1) and was pre-registered at https://osf.io/abf6q/ (see the Deviation from Registration section in Supplementary Material 2). All scripts and stimuli are available at https://osf.io/4zvkm/.

Participants. The sample size of this study was determined in a dynamic way (Schönbrodt, Wagenmakers, Zehetleitner, & Perugini, 2017). Specifically, we kept collecting data until strong evidence was obtained for the critical hypothesis (i.e., $BF_{10} \geq 10$ for the interaction between Self-Relevance X Valence on RT data) or the critical null hypothesis (i.e., $BF_{10} \leq 0.1$ for the interaction). In total, 46 college students (27 females, age: 20.91 ± 2.58) were recruited. Four participants were excluded from data analysis because of procedural failures, and one additional participant was excluded from analysis of the shape-categorization task because of zero accuracy performance in one condition.

Stimuli and Tasks. The experiment was conducted on a PC with a 22-in CRT monitor (1024×768 at 100Hz) using Matlab (2016a, MATLAB) and PsychToolbox-3 (Brainard, 1997). All stimuli were displayed in white against a grey background. Participants carried out the experiment individually in a quiet testing room. They first completed the perceptual-matching task with 48 practice trials, followed by three blocks of 120 experimental trials. After that, they completed the shape-categorization task with 6 blocks of 144 trials, with five short interleaved matching blocks of 48 trials (see Figure 2A). To avoid forming shape-key associations in the two types of categorization task, two pairs of buttons were used, one pair for each categorization task. The associations between buttons and categories (Good/Bad, Self/Other) were counterbalanced across participants. After finishing the experimental tasks, participants completed a series of questionnaires that are not reported here (see Supplementary Material 2).

Perceptual-Matching Task. Prior to the task, participants were asked to select a gender-matched forename from a list of common names for people they did not know personally (i.e., stranger condition). One of four geometric shapes (square, diamond, trapezoid, circle) was then assigned to a good or bad aspect of the participant and the stranger (good-self, bad-self, good-other, bad-other). For example, a participant was told, "a square represents the good-self, the morally good aspect of yourself; a diamond represents the bad-self, the immoral aspect of yourself; a trapezoid with a good-other (i.e., the morally good aspect of the stranger [replaced with the name participant had chosen]); and a circle with a bad-other (i.e., the immoral aspect of the stranger"). The shape-label assignment and the order of presentation of shape-label associations were counterbalanced across participants. The instructions were presented until participants pressed the space bar to begin the practice phase. The shape-label learning phase took approximately 1 minute to complete. Following the learning phase, participants immediately carried out the shape-label matching task to judge whether a shape-label pair, which was presented for 100 ms in the center of the screen, matched or mismatched the previously learned associations (see Figure 2B). The same four shapes were used throughout all the experimental trials. The shapes were presented with $3.7^{\circ} \times 3.7^{\circ}$ of visual angle and the labels with $3.6^{\circ} \times 1.6^{\circ}$ of visual angle above and below a central fixation cross with $0.8^{\circ} \times 0.8^{\circ}$ of visual angle. The distance between the center of the shape or the label and the fixation cross was 3.5º of visual angle.

Shape-Categorization Task. Following the perceptual-matching task, participants immediately carried out the shape-categorization task, in which a shape with 3.7º × 3.7º of visual angle was presented for 100 ms in the centre of the screen and participants were instructed to discriminate the stimulus based on its identity (self vs. other) or valence (good vs. bad) in different blocks (see Figure 2C). The order of the blocks (i.e., self vs. other, good vs. bad) was counterbalanced across participants.

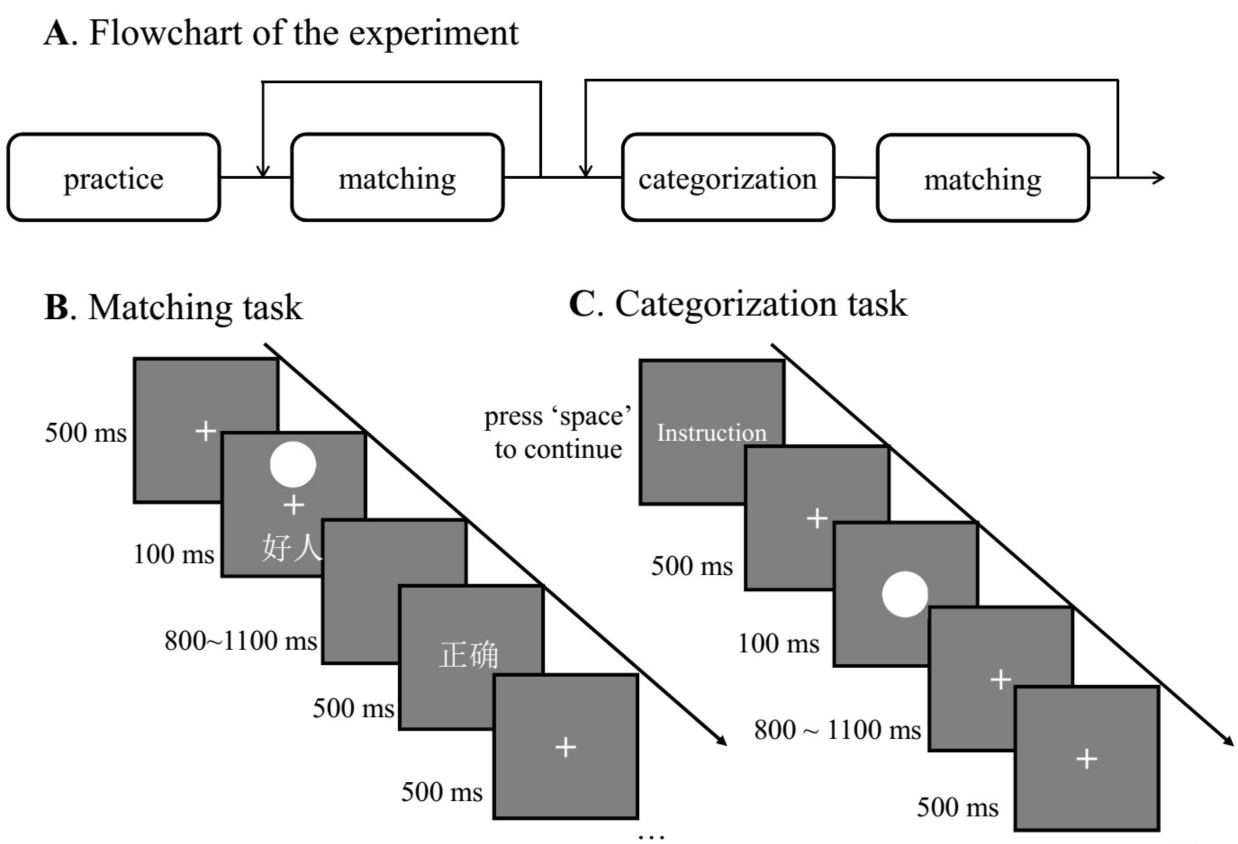

Figure 1. Flowchart of the experiment. (A) The general procedure of the experiment: participants first completed the perceptual-matching task with 48 practice trials, followed by three blocks of 120 experimental

trials. After that, they immediately completed the shape-categorization task with 6 blocks of 144 trials, with intertwined five small matching blocks of 48 trials; (B) In the perceptual-matching task, each trial began with the presentation of a central fixation cross for 500 ms, followed by a shape-label pairing for 100 ms, and a blank screen was shown for 800-1100 ms, during which participants were encouraged to judge whether the shape-label pair matched as quickly and accurately as possible by pressing one of two response buttons with the index or middle finger of the right hand, then, a feedback message, presented in white words ("correct" or "incorrect") against a grey background, was given in the centre of the screen for 500 ms following a response, or a message "too slow" was presented to remind participants to accelerate if no response was made within the response window; (C) In the shape-categorization tasks, each block began with a categorization cue (identity-based task or valence-based task) appeared in the centre of the screen, each trial started with a central fixation for 500 ms, replaced by a shape for 100 ms, then, a fixation cross was presented for 800 ~ 1100 ms, during which participants were encouraged to make a response as quickly and accurately as possible by pressing one of the two keys on the keyboard with the index or middle fingers of the right hand.

Data Analyses.

The data were first cleaned by R 3.5.3 (R Core Team, 2018) to remove trials with RTs less than 200 ms. This eliminated 0.2% of the trials in the matching task, and 0.05% of the trials in the categorization task. The sensitivity (*d* prime) of shape stimuli in the matching task was measured using a signal detection approach in which the performance in each matching condition was combined with that in the mismatching condition with the same shape to form a measure of *d* prime (Sui et al., 2012). We used the averaged reaction times from each condition as the measure of RTs (Sui et al., 2012). Note that the distribution of raw RTs were not normally distributed, but a recent simulation study showed that transformation of RT data does not necessarily improve statistical power (Schramm & Rouder, 2019).

ANOVAs for the Matching Task and the Categorization Task. The summary data (*d*-prime, accuracy, and mean RTs of each condition for each participant) were analyzed using JASP 0.10.0.0 (C.-P. Hu, Kong, Wagenmakers, Ly, & Peng, 2018; Love et al., 2019;

Wagenmakers et al., 2018). We tested the self-prioritization effect and the valence effect using both Frequentist repeated measures ANOVAs (rmANOVA) and the Bayes factor (BF) version. For the Bayes Factor analysis, we used default priors and interpreted BFs based on Jeffreys (Jeffreys, 1961; Wagenmakers et al., 2018), See **Supplementary Material 2** for details. To be succinct, we only report BFs and effect sizes for effects that were supported by the data, the full results (F-values and p-values) can be accessed from the online JASP files. We used RainCloud plots (Allen, Poggiali, Whitaker, Marshall, & Kievit, 2019) to visualize the results.

Cross-Task Analysis. To test the cross-task robustness of the self-relevance and valence effects, we further estimated the cross-task correlation of the self-relevance effect (good-self vs. good-other) and the valence effect (good-self vs. bad-self), see Supplementary Material 2.

Diffusion Modelling. To examine the processes underpinning task performance, we used a drift-diffusion model (DDM) to decompose the RT and accuracy data. We estimated the parameters of the DDM using a hierarchical Bayesian model (HDDM) (http://ski.clps.brown.edu/hddm_docs; Wiecki et al., 2013) , with a default group prior roughly matching the parameter values reported by (Matzke & Wagenmakers, 2009). Based on previous research (e.g., Golubickis et al., 2017) , we fixed the boundary threshold ***a*** because it has been suggested that boundary separation should remain constant throughout a task when the luminance of the stimuli is constant across the trials.

Deviating from the pre-registration, we used the response coded approach (i.e., the top and lower boundary is defined based on the response given, see the Deviations from Pregistration in Supplementary Material 2. Markov Chain Monte-Carlo (MCMC) chains were used to estimate the posterior distribution of the parameters. The convergence of MCMC chains was checked. Also, we conducted a model comparison with additional models in which the parameters *v* and *z* were free to vary, using the Deviance Information Criterion (DIC) and posterior prediction check (PPC). Bayesian model comparisons showed that the best fitting model required the three-parameter model. We then extracted the parameters for each condition and tested the Bayesian hypothesis by analysing the posterior probability density of the parameters across the conditions. If more than 95% of the posterior density exceeded zero, the effect was regarded as statistically significant. See Supplementary Material 2 for details of HDDM modeling.

Results

All the raw data (in csv format), detailed results (in JASP format), and related R scripts are available at https://osf.io/4zvkm/.

Perceptual-Matching Task.

ANOVAs. As described in our pre-registration, we focused on the matching trials for RTs. Repeated measures ANOVAs on RTs showed strong evidence for the interaction between Self-relevance X Valence, $BF_{10} = 68.04$, $BF_{incl} = 133.9$, $\omega^2 = 0.05$. There was also overwhelming evidence for the main effect of Valence, $BF_{10} = 8.26e+6$, $BF_{incl} = 2.3e+8$, $\boldsymbol{\omega^2} = 0.16$, but no strong evidence for the main effect of Self-relevance. (**Figure 2A**, upper panel). Planned contrasts showed good-self (637 ± 63 ms) responses were faster than bad-self responses (720 ± 70 ms), BF_{-0} = 1.19e + 8, Cohen's *dz* = -1.299, 95% CI[-1.708 -0.883], and good-other (681 ± 81 ms) responses were faster than bad-other responses (707 ± 70 ms), BF_{-0} = 4.01, Cohen's *d* = -0.367, 95% CI[-0.677 -0.052]. In addition, good-self was faster than good-other, BF_{-0} = 35.50, Cohen's *d* = -0.515, 95% CI[-0.834 -0.190], but there was no evidence for a difference between the bad-self and bad-other (see **Figure S6** for robustness check of Bayesian *t*-tests.)

The results of the *d*-prime analysis were largely similar to the RT data. The evidence for the interaction between Self-Relevance X Valence was strong, BF_{10} = 70.90, BF_{incl} = 24.7, ω^2 = 0.01. Evidence for the main effect of Valence was mixed, BF_{10} = 0.90, BF_{incl} = 8.5, $\boldsymbol{\omega^2}$ **=** 0.02, and no evidence for the main effect of Self-relevance was observed. (**Figure2 A**, lower panel**)**. Planned contrasts showed that there was a larger *d*-prime for good-self (2.33 ± 0.71) than either bad-self (1.80 ± 0.66), BF_{+0} = 472.80, Cohen's *d* = 0.664, 95% CI[0.326 0.995], or good-other (1.91 ± 0.75), BF_{+0} = 7.38, Cohen's *d* = 0.411, 95% CI[0.094 0.74]. No evidence for the other two contrasts of interest emerged. (see **Figure S6** for robustness check of Bayesian *t*-tests.)

***Diffusion Modelling*.** The posterior distributions showed evidence of a stimulus bias indexed by the drift rate (*v*) on matching trials, such that information uptake was faster for good-self than either bad-self ($P_{\text{posterier}}$ (match-good-self > match-bad-self) = 1) or good-other ($P_{\text{posterier}}$ (match-good-self > match-good-other) = 1) (**Figure 3A**). These effects were not observed on non-matching trials (see **Figure S8**). The analysis of the starting point (*z*) showed a prior bias toward matching responses (*z* = 0.5), $P_{\text{posterier}}$ (*z* > 0.5) = 1. Analyses of the non-decision time (t_0) yielded no differences between conditions.

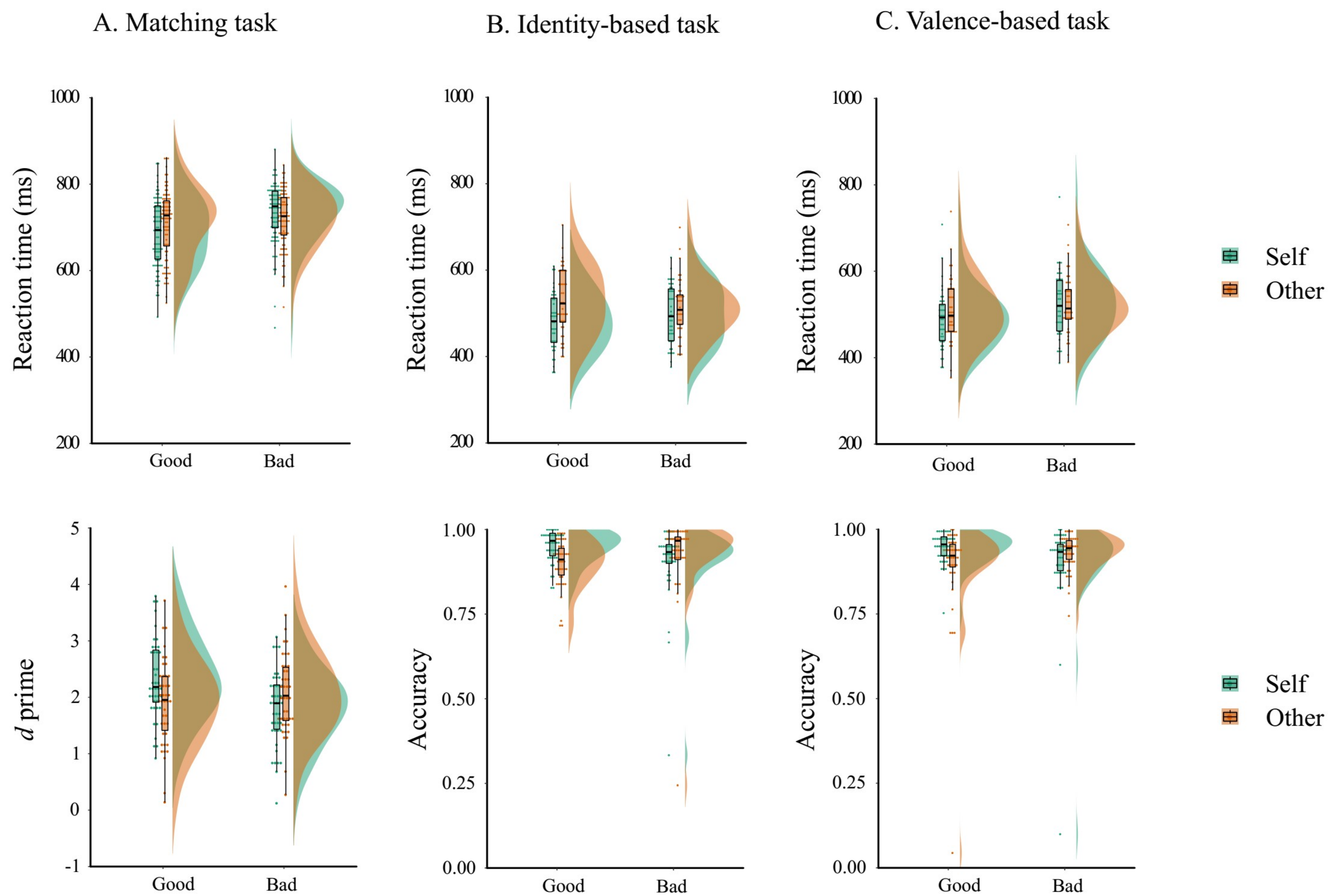

Figure 2. Reaction times and *d* prime as a function of Target and Valence. (A), Reaction times (upper) and *d* prime (lower) for perceptual-matching task; (B), Reaction times (upper) and accuracy (lower) for identity-based categorization task; (C), Reaction times (upper) and accuracy (lower) for identity-based categorization task.

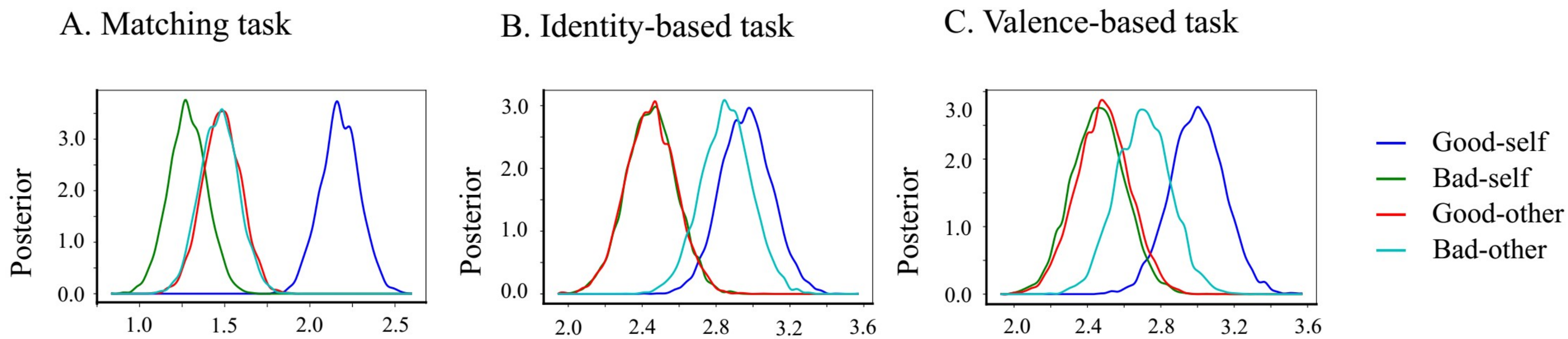

Figure 3. Drift rates as a function of Target and Valence. (A) perceptual-matching task; (B), identity-based categorization task; (C), identity-based categorization task.

Shape-Categorization Task.

***ANOVAs*.** The three-way rmANOVA on RTs revealed a Self-relevance X Valence interaction, BF_{10} = 19.60, BF_{incl} = 54.5, ω^2 = 0.008, and main effects of Valence, BF_{10} = 4.28, BF_{incl} =407, ω^2 = 0.009, and Self-Relevance, BF_{10} =12971, BF_{incl} = 879324, ω^2 = 0.028 (**Figure 2B and 2C**, upper panel). Also, there was an interaction between Task type X Valence, between Task Type X Self-relevance, but no evidence for the main effect of Task Type or the three-way interaction (see online JASP files). We therefore collapsed the data across Task Type and compared the pairs of conditions of interest. Results showed faster responses to the good-self (484 ± 62) than both the good-other, (519 ± 70), BF_{-0} = 57, Cohen's *d* = -0.684, 95% CI[-1.021 - 0.339], and bad-self (509 ± 68), BF_{-0} = 23.90, Cohen's *d* = -0.496, 95% CI[-0.819 -0.169]. No other differences were observed (see **Figure S7** for robustness check of Bayesian *t*-tests.)

The three-way rmANOVA on accuracy showed strong evidence for the interaction between Self-relevance X Valence, BF_{10} = 256.50, BF_{incl} = 14.7, ω^2 = 0.06. But only mixed evidence for the main effect of Self-relevance, and no evidence for the main effect of Valence. The evidence for all other interactions were absent (see online JASP files). After collapsing data across the two categorization tasks, planned contrasts revealed that responses to the good-self (0.947 ± 0.037) were more accurate than either the bad-self (0.902 ± 0.1), BF_{+0} = 17.9, Cohen's *d* = -0.478, 95% CI[0.152, 0.798], or good-other (0.89 ± 0.088), BF_{+0} = 106.70, Cohen's *d* = 0.589, 95% CI[0.253 0.917] (**Figure 2B and 2C**, lower panel). No other differences emerged (see **Figure S7** for robustness check of Bayesian *t*-tests.)

Diffusion Modelling*.** The HDDM analysis of the shape-categorization tasks revealed that the drift rate (v***) was higher for good-self than for good-other in both the valence-based task ($P_{posterier}$ (Good-self > Good-other) > 0.994) and the identity-based task ($P_{posterier}$ (Good-self >

Good-other) > 0.996). The drift rate was also higher for good-self than for bad-self in both the valence-based ($P_{\text{posterier}}$ (Good-self > Bad-self) = 0.99) and identity-based tasks ($P_{\text{posterier}}$ (Good-self > Bad-self) = 0.99) (see **Figure 3B, 3C**, and **Table S4**).

For the starting point, there was no strong evidence for bias toward positive or negative valence in the valence-based task ($P_{\text{posterier}}$ (bias > 0.5) = 0.69), but there was a strong evidence for a bias toward the self compared to other in the identity-based task ($P_{\text{posterier}}$ (bias > 0.5) = 1.00) (see **Table S4**). Analyses of the non-decision processes (t_0) showed that these activities were longer to good-self than good-other, $P_{\text{posterier}}$ (good-self > good-other) = 0.99 (see **Table S4**).

Discussion

Here we manipulated stimulus properties based on identity-relevant valence (i.e., good me, bad me, good other, bad other) to examine which facet of the self is crucial to the emergence of the self-prioritization effect. The results demonstrated a robust 'good-self' prioritization effect in perceptual decision-making, regardless of task type (i.e., perceptual-matching or shape-classification). Specifically, compared to other shape-label stimulus combinations, the good-self yielded the most potent benefits during decisional processing. An HDDM analysis further revealed that the good-self association facilitated performance by improving the efficiency of visual processing. These findings suggest that, as a core identity-related component, stimuli associated with the good-self are prioritized during perceptual decision-making (Sedikides & Strube, 1997).

One candidate explanation for the 'good-self' prioritization effect lies in the 'integrative' self view (Sui & Humphreys, 2015), such that activation of the self-concept facilitates the binding of external stimuli to established self-representations and subsequently leads to prioritized responses to self-related stimuli. However, it remains unclear which aspect of the self-representation is critical to the emergence of this effect. In this respect, recent studies have suggested that the positive aspect of the self-concept may comprise the core self-representation (i.e., true self, see Strohminger, Knobe, & Newman, 2017), consistent with the traditional positive self-bias account (Greenwald, 1980). Corroborating this viewpoint, the current results confirm that self-prioritization during perceptual matching is greater when stimuli are paired with the good- than bad-self. A competing explanation is that the results may reflect a congruency effect (i.e., positive valence is more congruent with the self, while negative valence with non-self). If this were the case, however, then we would observe faster responses to the congruent pairs, both the good-self and the bad-other, than the incongruent pairs, the bad-self and the good-other (see **Supplementary Material 3**).

The results in the present study extend previous work on self-prioritization in a number of interesting ways. First, information uptake was faster when stimuli were paired with the good-self (vs. bad-self or good-other), an effect that emerged in both perceptual-matching and shape-categorization tasks. Going beyond perceptual-matching in which the self-relevance of stimuli must be considered to successfully perform the task (Sui et al., 2012), a good-self prioritization effect emerged when only the shape of the stimuli were task relevant. Second, the magnitude of self-prioritization was modulated by the aspect of the self-concept with which information was associated. That is, rather than the self-concept exerting a basic facilitatory effect on stimulus processing, performance was enhanced when information was tagged with an identity-based aspect of the self, the good-self. Third, to date, the effects of self-enhancement have largely been confined to aspects of higher-level cognition, such as attributions (Pronin, 2008; Sedikides & Strube, 1997), social evaluation, and memory (X. Hu et al., 2015). In contrast, the current results provided evidence that self-enhancement also occurs during the early stages of processing, notably perceptual decision-making. Finally, using computational modeling, we demonstrated that self-prioritization (i.e., good-self prioritization) is underpinned by differences in the efficiency of visual processing (i.e., rate of information uptake) during decision-making (Sui & Humphreys, 2015).

Limitations

The generalizability of the current findings may be limited by the sample (young, healthy Chinese college students) that was tested. Also, we assumed that participants had a positive self-concept (Hepper, Sedikides, & Cai, 2011), resulting in better performance for stimuli tagged with the good-self compared to the bad-self. This assumption should be examined in future research, particularly focusing on individuals with a negative self-concept.

Author contributions

C-P. Hu & J. Sui designed the study, C-P. Hu collected the data and analysed data of pilot study, C-P. Hu & Y. Lan collected the data and analysed the data of confirm study, C-P. Hu drafted the manuscript, all authors read and approved the current manuscript.

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