

1 Self-relevance modulates the priorization of the good character in perceptual matching

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## Abstract

Morality is central to social life, moral character is central to morality. Researchers assume that moral character information is prioritized in perceptual process, yet the evidence is scarce. In a series of experiments, we examined the effect of immediately acquired moral character information on perceptual matching. Participants first learned the association between moral characters (labels) and visual cues (shapes), then performed a shape-label perceptual matching task. The results revealed that shapes associated with good character were prioritized, as compared to shapes associated with neutral or bad characters. This effect was robust after changing the words for label or using diagnostic behavioral as an proxy of moral character. Also, this pattern was robust when changing simultaneous presentation to sequential presentation. We then examined two approximate explanations for this effect: value-based prioritization versus social-categorization based prioritization. We manipulated the identity of moral character explicitly and found that good character effect was strong when it refers to the self but weak or non-exist when it refers to a stranger. In further experiments where both identity or moral character information were presented but only one of them served as task-relevant stimuli, we found that task-irrelevant good character facilitate response to self but slow down the response to stranger and that task-irrelevant self-referential information facilitated response to good character but task-irrelevant stranger-referential information slowed down response to good character. Together, these results suggested that people are sensitive to who is the good character, but less sensitive to who is the neutral or bad character. When the identity information is ambiguous, people may spontaneously referring the good character as self. These results added new evidence for the social vision and suggested the advantage of good character depends on the self-relevance.

*Keywords:* Perceptual decision-making, Self positivity bias, moral character

Word count: X

Self-relevance modulates the prioritization of the good character in perceptual matching

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## Introduction

[quotes about moral character]

social vision → moral vision → two competing explanations (value-based vs. true-self-based) → true-self is not perspective free but self-centered.

[morality is central to social life, moral character is the central of morality] People experience a substantial amount of moral events in everyday life (e.g., Hofmann, Wisneski, Brandt, & Skitka, 2014). Whether we are the agent, target, or a third party of a moral event, we always judge moral behaviors as “right” or “wrong,” and by doing so, we judge moral character of people as “good” or “bad” (Uhlmann, Pizarro, & Diermeier, 2015). Moral character is so important in social life that a substantial part of people’s conversation are gossiping others’ moral character (or, reputation) (e.g., Dunbar, 2004). Also, evidence from studies of person perception and social evaluation revealed that morality is a basic dimension for social evaluation and it is weighed more than traits from other dimensions such as competence and sociability (Abele, Ellemers, Fiske, Koch, & Yzerbyt, 2020; Goodwin, 2015; Goodwin, Piazza, & Rozin, 2014). The importance of moral character may have been internalized to individuals’ self-concept and the positive moral self is the most important aspect of identity (e.g., Strohminger, Knobe, & Newman, 2017), and moral character is a standard we used to evaluate our in-group members and distinguish out-group members (Ellemers, 2018).

[No real perceptual studies on moral character] Given the importance of moral character, people often assume that moral character related information are prioritized in human information processing system, especially ‘bad’ agents (e.g., the introduction part of

Siegel, Mathys, Rutledge, & Crockett, 2018). A scrutiny of the literature, however, revealed few direct evidence. For example, while Schupp et al. (2004) and Ohman, Lundqvist, and Esteves (2001) were cited to support this view, they are using facial expressions as stimuli that do not contain any moral meaning. Skowronski and Carlston (1989), Fiske (1980), and Baumeister, Bratslavsky, Finkenauer, and Vohs (2001) were also cited as evidence, but they were not referring to moral character in specific but using negative social traits, which include many other traits. For instance, Pratto and John (1991) focused on the desirability of personal traits, which is not specific to moral character either. While Vanneste, Verplaetse, Van Hiel, and Braeckman (2007) studied the attentional grabbing effect of facial expressions when agents decided not to cooperate, the mechanism of the effect, however, could not be attributed to uncooperativeness *per se*, because participants who performed the dot-detection task have no idea about the moral character and can have very different interpretations of those facial expressions. In short, though researchers in the field assumed that moral character, especially the bad one, is prioritized in information processing, direct evidence is scarce. This issue is not limited to moral character but common in person perception studies. As Freeman and Ambady (2011) put it, most studies in person perception didn't try to explain the perceptual process itself, rather, they are trying to explain the higher-order social cognitive processes that come after. Therefore, it remains unclear (1) whether moral character related information are prioritized in information processing (e.g., perception) and, if yes, (2) what are the underlying mechanisms of the prioritization effect.

[Challenge: operationalization of moral character in laboratory settings] The scarcity of studies on low-level information process of moral character is not without reasons. When trying to study moral character's effect on information process (e.g., perception), one big challenge lies in the difficulty to operationalize the moral character. Morality is defined by context. Whether a behavior should be judged as moral or immoral depends on a number of factors such as intention, consequences (Cushman, Young, & Hauser, 2006; Young,

Cushman, Hauser, & Saxe, 2007). Also, whether a behavior is moral relevant depends on cultural and social norm (Haidt, 2007; Rai & Fiske, 2011). These contextual factors, when studied in laboratory settings, have to be carefully controlled and manipulated by providing complex verbal information. These complex verbal information, however, does not suit most classic cognitive paradigms where stimuli are presented shortly and participants are required to make quick decisions.

To solve this issue, two approaches emerged in the last decade. The first approach used direct associative learning. For example, Shore and Heerey (2013) asked participants first interact with a stranger, who was represented by a face on the screen. Participants formed impression of that person through interaction and judge him/her as trustworthy or not. After getting such impression, participants then finished a attention blink task where the faces were used as stimuli. Their findings revealed that faces associated with cooperative interaction history are preferentially processed in the pre-attention stage.

Another approach used indirect associative learning, where participants first associate visual stimuli (e.g., faces) with descriptions of a person's behaviors, then perform a task that examine the differences between visual stimuli that associated with different behaviors. For example, E. Anderson, Siegel, Bliss-Moreau, and Barrett (2011) associated faces with different behaviors (both negative and neutral behaviors from both social and nonsocial domains) and then asked participants to perform a binocular rivalry task, where a face and a building were presented to each eye and participant were required report the content of their vision by pressing buttons. They found that faces associated negative social behaviors were dominant for longer time in the visual awareness than faces associated with other types of behaviors (but see Stein, Grubb, Bertrand, Suh, & Verosky, 2017). Eiserbeck and Abdel Rahman (2020) combined indirect associative learning with attention blink paradigm, where neutral faces were associated with sentences about neutral or negative trust behaviors and asked participants to perform a attention blink task. They also found that neutral faces associated with negative behavior were processed

preferentially. The indirect associative learning paradigm had been developed primarily for affective meanings, and these studies found that building such association requires minimal behavioral information (Bliss-Moreau, Barrett, & Wright, 2008; Falvello, Vinson, Ferrari, & Todorov, 2015; Todorov & Olson, 2008). A similar approach has been used to explore the prioritization of self-related information (Sui, He, & Humphreys, 2012), where more abstract concepts (person labels, e.g., “self,” “friend,” “stranger”) and simpler visual cues (geometric shapes, e.g., triangle, circle, or square) were used. This simpler shape-label associative learning task produced robust self-prioritization effect.

Both direct and indirect associative learning paradigms are consistent with the dynamic interactive model of person perception (Freeman & Ambady, 2011). The dynamic interactive model proposed that the perceived personal traits are interactively linked with behavior and sensory stimuli. By activating some sensory stimuli, some person traits can be activated. The associative learning task reverse engineering the process and linking the personal traits (moral character in our case) with new visual stimuli, therefore created a temporary but direct link between personal traits and visual stimuli. After creating such associations between different traits and different visual cues, we can then test the newly established trait-cue associations by different cognitive tasks and examine the instantly learned associations’ influence on cognitive processing.

[The current study] The current study was designed to investigate the perceptual process of moral character by using the shape-label associative learning task. This paradigm has two major advantages over face-based indirect associative learning tasks. First, it only used a few number of labels that represent different moral characters, therefore control individual differences in interpreting moral meaning of behaviors. Second, it uses non-social visual stimuli as cues, avoided the idiosyncratic features brought by using faces. Besides, the simplicity of the task allows it to be easily combined with other cognitive tasks. Using this shape-label associative learning and perpetual matching task, the current study aimed at answering two questions mentioned above: (1) whether moral

character related information are prioritized, if so, what is the exact pattern; (2) what is the potential explanation for such pattern.

To investigate the first issue and validate that moral character concepts activated moral character as a social cue, we designed four experiments to explore and validate the paradigm. The first experiment directly adopted associative paradigm from Sui, He, and Humphreys (2012) and changed labels from “self,” “friend,” and “stranger” to “good-person,” “neutral-person,” and “bad-person.” In the follow-up studies, we tested other character labels that have similar moral meaning (“kind-person,” “neutral-person,” and “evil-person”). In the third experiments, as in E. Anderson, Siegel, Bliss-Moreau, and Barrett (2011), we asked participants to learn associations between three different diagnostic behaviors and three different names, and then use the names as character labels for the associative learning. Finally, we also tested that simultaneously present shape-word pair and sequentially present labels and shapes. All of these four experiments showed a consistent results, that is, the visual cues that associated with positive moral character were prioritized.

Although the available studies agree that social/moral information can enhance the saliency of the sensory stimuli, yet the reported direction of the effect is not consistent. For instance, there are two studies reported a negativity effect where neutral faces associated with negative social behavioral were processed better than neutral faces that associated with neutral behaviors (E. Anderson, Siegel, Bliss-Moreau, & Barrett, 2011; Eiserbeck & Abdel Rahman, 2020; but see Stein, Grubb, Bertrand, Suh, & Verosky, 2017). The underlying reasons for the prioritization was usually attributed to affective meaning of the negative behaviors, which, in essence, is a threatening effect. In contrast, there was one study reported a positivity effect, where faces associated with positive interaction history were prioritized over faces associated with neutral or negative interaction history. And the positivity effect was attributed to a value-based information process (Shore & Heerey, 2013).

The direction of the effect leads to different underlying explanations. The negativity effect usually explained by the evolutionary adoptive mechanism where the threatening feature were prioritized. However, accumulating evidence supported the view that negativity effect, especially those related to affective stimuli, are prioritized because of the low-level physical features, e.g., low frequency feature in the facial expression (see a recent review, Pool, Brosch, Delplanque, & Sander, 2016). This is reflected in the pattern that threatening stimuli are prioritized in detection task, e.g., dot-probe task. In the current study, because all visual stimuli share similar physical features and we did not using detection task but matching task, therefore, it's not surprising that we didn't found a threatening effect.

The positivity effect, on the other hand, appeared later in the processing stage and were attributed to its rewarding value (we limit the value-based account to rewarding value). The value based account is an appealing explanation, there were strong evidence supporting the view that positive emotional stimuli are prioritized (Pool, Brosch, Delplanque, & Sander, 2016). For example, Brian A. Anderson, Laurent, and Yantis (2011) found that stimuli associated with higher reward could be found more easily in a visual search task. The follow-up studies confirmed that value-based prioritization if a robust effect (Brian A. Anderson, 2019). In our experiments, the good character label "good person" may represent an indirect but positive value. The value of good others had been found in previous survey (Abele & Wojciszke, 2007).

When applying to social information such as moral character, both the value-based account and the threatening model ignored the social meaning of the stimuli. Increasing evidence supported the view that social meaning of visual stimuli (e.g., social groups) also impacts our information processing, including perception (Freeman & Ambady, 2011; Xiao, Coppin, & Bavel, 2016). Social categorization theory stated that we perceiving others based on whether or not belong to "us" (Turner, Hogg, Oakes, Reicher, & Wetherell, 1987). In other words, we may view a person with good character as an in-group member, while a



bad person as them (Ellemers, 2018). If moral judgment is an implicit social categorization process (DeScioli, 2016; McHugh, McGann, Igou, & Kinsella, 2019), and if social categorization impact our visual perception (Xiao, Coppin, & Bavel, 2016), then we can infer the prioritization of good character may be the results of a social categorization process, i.e., we regard good person as an natural extension of the self.

However, the above four experiments could not distinguish between these possibilities, because the “good-person” label was not explicit about the identity. Therefore, the label “good person” could both be rewarding and be categorized as in-group member. Previous studies using associative learning paradigm revealed that both rewarding stimuli (e.g., Sui, He, & Humphreys, 2012) and in-group information (Enock, Hewstone, Lockwood, & Sui, 2020) are prioritized.

[Distinguish two explanations by make self salient, exp3a, 3b, 6b] Though both two the value-based attention and moral-based categorization accounts can explain the positivity effect found in first four experiments (i.e., prioritization of “good-person,” but not “neutral person” and “bad person”), they have different prediction if the experimental design include both identity and moral valence where the valence (good, bad, and neutral) conditions can describe self or other. In this case the identity become salient and participants are less likely to spontaneously identify a good-other as the extension of self, but the value of good-person still exists. Actually, the rewarding value of good-other might be even stronger than good-self because the former indicate potential cooperation and material rewards, but the latter merely confirmed one’s personal belief. This means that the social categorization theory predicts participants prioritize good-self but not good-other, while value-based attention theory predicts both are prioritized, or maybe good-other are even more prioritized. Also, as in Hu, Lan, Macrae, and Sui (2020), people may also only identify with good-self instead of bad self. That is, people will show a unique pattern of self-identification: only good-self is identified as “self” while all the others categories were excluded.

We introduced identity (self vs. other) as an addition independent variable in exp 3a, 3b, and 6b. Now the moral valence is orthogonal to the identity. We found that (1) good-self is always faster than neutral-self and bad-self, but good-other only have weak to null advantage to neutral-other and bad-other. which mean the social categorization is self-centered. (2) good-self's advantage over good other only occur when self- and other- were in the same task. i.e. the relative advantage is competition based instead of absolute. These three experiments suggest that people more like to view the moral character stimuli as person and categorize good-self as an unique category against all others. A three-level Bayesian generalized linear mixed effect model showed that there was no effect of valence when the identity was other. This results showed that value-based attention was not likely the mechanism behind the pattern we observed in first four experiments. However, it is still unclear why good-self was prioritized. Besides the social-categorization explanation, it's also possible that good self is so unique that it is prioritized in all possible situation and therefore is not social categorization *per se*.

[what we care? valence of the self exp4a or identity of the good exp4b?] We went further to disentangle the good-self complex: is it because the special role of good-self or because of social categorization. We designed two complementary experiments. in experiment 4a, participants only learned the association between self and other, the words “good-person,” “neutral person,” and “bad person” were presented as task-irrelevant stimuli, while in experiment 4b, participants learned the associations between “good-person,” “neutral-person,” and “bad-person,” and the “self” and “other” were presented as task-irrelevant stimuli. These two experiment can be used to distinguish the “good-self” as anchor account and the “good-self-based social categorization” account. If good-self as an anchor is true, then, in both experiment, good-self will show advantage over all other stimuli, and there will be no other effects. More specifically, in experiment 4a, where only the self-relevance is task-relevant, there will be advantage for good as task-irrelevant condition than the other two self conditions, while there is no other effects;

in experiment 4b, in the good condition, there will be an advantage for self as task-irrelevant condition over other as task-irrelevant condition, and no other effects. If good-self-based social categorization is true, then, the prioritization effect will depend on whether the stimuli can be categorized as the same group of good-self. More specifically, in experiment 4a, there will be a good effect in self conditions, this prediction is the same as the “good-self as anchor” account, but also, it predicts a reverse good effect in other condition because good and other are in conflict in terms of social-categorization, this prediction is different from the “good-self” anchor account; however, for experiment 4b, it predicts no identity effect in the good-person condition because both self and other are in the good group.

[Good self in self-reported data] As an exploration, we also collected participants’ self-reported psychological distance between self and good-person, bad-person, and neutral-person, moral identity, moral self-image, and self-esteem. All these data are available (see Liu et al., 2020). We explored the correlation between self-reported distance and these questionnaires as well as the questionnaires and behavioral data. However, given that the correlation between self-reported score and behavioral data has low correlation (Dang, King, & Inzlicht, 2020), we didn’t expect a high correlation between these self-reported measures and the behavioral data.

## Disclosures

We reported all the measurements, analyses, and results in all the experiments in the current study. Participants whose overall accuracy lower than 60% were excluded from analysis. Also, the accurate responses with less than 200ms reaction times were excluded from the analysis.

All the experiments reported were not pre-registered. Most experiments (1a ~ 4b, except experiment 3b) reported in the current study were first finished between 2013 to

2016 in Tsinghua University, Beijing, China. Participants in these experiments were recruited in the local community. To increase the sample size of experiments to 50 or more (Simmons, Nelson, & Simonsohn, 2013), we recruited additional participants in Wenzhou University, Wenzhou, China in 2017 for experiment 1a, 1b, 4a, and 4b. Experiment 3b was finished in Wenzhou University in 2017. To have a better estimation of the effect size, we included the data from unreported data in our three-level models (experiment 5, 6a, 6b) (See Table S1 for overview of these experiments).

All participant received informed consent and compensated for their time. These experiments were approved by the ethic board in the Department of Psychology, Tsinghua University.

## General methods

### Design and Procedure

This series of experiments studied the perceptual process of moral character, using the social associative learning paradigm (or tagging paradigm)(Sui, He, & Humphreys, 2012), in which participants first learned the associations between geometric shapes and labels of person with different moral character (e.g., in first three studies, the triangle, square, and circle and good person, neutral person, and bad person, respectively). The associations of the shapes and label were counterbalanced across participants. After remembered the associations, participants finished a practice phase to familiar with the task, in which they viewed one of the shapes upon the fixation while one of the labels below the fixation and judged whether the shape and the label matched the association they learned. When participants reached 60% or higher accuracy at the end of the practicing session, they started the experimental task which was the same as in the practice phase.

The experiment 1a, 1b, 1c, 2, 5, and 6a shared a 2 (matching: match vs. nonmatch) by 3 (moral character: good vs. neutral vs. bad person) within-subject design. Experiment

1a was the first one of the whole series studies and found the prioritization of stimuli associated with good-person. To confirm that it is the moral character that caused the effect, we further conducted experiment 1b, 1c, and 2. More specifically, experiment 1b used different Chinese words as labels to test whether the effect only occurred with certain words. Experiment 1c manipulated the moral valence indirectly: participants first learned to associate different moral behaviors with different Chinese names, after remembered the association, they then performed the perceptual matching task by associating names with different shapes. Experiment 2 further tested whether the way we presented the stimuli influence the effect of valence, by sequentially presenting labels and shapes. Note that part of participants of experiment 2 were from experiment 1a because we originally planned a cross task comparison. Experiment 5 was designed to compare the effect size of moral character and other importance social evaluative dimensions (aesthetics and emotion). Different social evaluative dimensions were implemented in different blocks, the moral character blocks shared the design of experiment 1a. Experiment 6a, which shared the same design as experiment 2, was an EEG experiment which aimed at exploring the neural correlates of the effect. But we will focus on the behavioral results of experiment 6a in the current manuscript.

For experiment 3a, 3b, and 6b, we included self-reference as another within-subject variable in the experimental design. For example, the experiment 3a directly extend the design of experiment 1a into a 2 (matching: match vs. nonmatch) by 2 (reference: self vs. other) by 3 (moral character: good vs. neutral vs. bad) within-subject design. Thus in experiment 3a, there were six conditions (good-self, neutral-self, bad-self, good-other, neutral-other, and bad-other) and six shapes (triangle, square, circle, diamond, pentagon, and trapezoids). The experiment 6b was an EEG experiment based on experiment 3a but presented the label and shape sequentially. Because of the relatively high working memory load (six label-shape pairs), experiment 6b were conducted in two days: the first day participants finished perceptual matching task as a practice, and the second day, they

finished the task again while the EEG signals were recorded. We only focus on the first day's data here. Experiment 3b was designed to separate the self-referential trials and other-referential trials. That is, participants finished two different types of block: in the self-referential blocks, they only responded to good-self, neutral-self, and bad-self, with half match trials and half nonmatch trials; in the other-reference blocks, they only responded to good-other, neutral-other, and bad-other.

Experiment 4a and 4b were design to explore the mechanism underlying the prioritization of good-self. In 4a, we only used two labels (self vs. other) and two shapes (circle, square). To manipulate the moral character, we added the moral-related words within the shape and instructed participants to ignore the words in the shape during the task. In 4b, we reversed the role of self-reference and moral character in the task: participant learned three labels (good-person, neutral-person, and bad-person) and three shapes (circle, square, and triangle), and the words related to identity, "self" or "other," were presented in the shapes. As in 4a, participants were told to ignore the words inside the shape during the task.

E-prime 2.0 was used for presenting stimuli and collecting behavioral responses. For participants recruited in Tsinghua University, they finished the experiment individually in a dim-lighted chamber, stimuli were presented on 22-inch CRT monitors and their head were fixed by a chin-rest brace. The distance between participants' eyes and the screen was about 60 cm. The visual angle of geometric shapes was about  $3.7^\circ \times 3.7^\circ$ , the fixation cross is of  $0.8^\circ \times 0.8^\circ$  visual angle at the center of the screen. The words were of  $3.6^\circ \times 1.6^\circ$  visual angle. The distance between the center of the shape or the word and the fixation cross was  $3.5^\circ$  of visual angle. For participants recruited in Wenzhou University, they finished the experiment in a group consisted of 3 ~ 12 participants in a dim-lighted testing room. Participants were required to finished the whole experiment independently. Also, they were instructed to start the experiment at the same time, so that the distraction between participants were minimized. The stimuli were presented on 19-inch CRT monitor. The

visual angles are could not be exactly controlled because participants' chin were not fixed.

In most of these experiments, participant were also asked to fill a battery of questionnaire after they finish the behavioral tasks. All the questionnaire data are open (see, dataset 4 in Liu et al., 2020). See Table S1 for a summary information about all the experiments.

## Data analysis

We used the `tidyverse` of `r` (see script `Load_save_data.r`) to preprocess the data. Results of each experiment were then analyzed using Bayesian hierarchical models.

We used the Bayesian hierarchical model (BHM, or Bayesian generalized linear mixed models, Bayesian multilevel models) to model the reaction time and accuracy data, because BHM provided three advantages over the classic NHST approach (repeated measure ANOVA or *t*-tests): first, BHM estimate the posterior distributions of parameters for statistical inference, therefore provided uncertainty in estimation (Rouder & Lu, 2005). Second, BHM, where generalized linear mixed models could be easily implemented, can use distributions that fit the distribution of real data instead of using normal distribution for all data. Using appropriate distributions for the data will avoid misleading results and provide better fitting of the data. For example, Reaction times are not normally distributed but right skewed, and the linear assumption in ANOVAs is not satisfied (Rousselet & Wilcox, 2019). Third, BHM provided an unified framework to analyze data from different levels and different sources, avoid the information loss when we need to combine data from different levels.

We used the `r` package `BRMs` (Bürkner, 2017), which used Stan (Carpenter et al., 2017) for the BHM analyses. We estimated the over-all effect across experiments with similar experimental design, instead of using a two-step approach where we first estimate parameters, e.g.,  $d'$  for each participant, and then use a random effect model meta-analysis

to synthesize the effect (Goh, Hall, & Rosenthal, 2016).

**Accuracy.** We followed practice of previous studies (Hu, Lan, Macrae, & Sui, 2020; Sui, He, & Humphreys, 2012) and used signal detection theory approach to analyze the accuracy data. More specifically, the match trials are treated as signal and the non-match trials are noise. As we mentioned above, we estimated the sensitivity and criterion of SDT by BHM (Rouder & Lu, 2005). Because the BHM can model different level’s data using a single unified model, we used a three-level HBM to model the moral character effect, which include five experiments: 1a, 1b, 1c, 2, 5, and 6a. Similarly, we modeled experiments with both self-referential and moral character with a three-level HBM model, which includes 3a, 3b, and 6b. For experiment 4a and 4b, we used two-level models for each separately. However, we could compare the posterior of parameters directly because we have full posterior distribution of parameters.

We used the Bernoulli distribution to model the accuracy data. For a single participant, we assume that the accuracy of  $i$ th trial is Bernoulli distributed (binomial with 1 trial), with probability  $p_i$  that  $y_i = 1$ .

$$y_i \sim \text{Bernoulli}(p_i)$$

and the probability of choosing “match”  $p_i$  at the  $i$ th trial is a function of the trial type:

$$\Phi(p_i) = \beta_0 + \beta_1 \text{IsMatch}_i$$

therefore, the outcomes  $y_i$  are 0 if the participant responded “nonmatch” on the  $i$ th trial, 1 if they responded “match.” We then write the generalized linear model on the probits (z-scores;  $\Phi$ , “Phi”) of  $p_i$ .  $\Phi$  is the cumulative normal density function and maps  $z$  scores to probabilities. In this way, the intercept of the model ( $\beta_0$ ) is the standardized false alarm rate (probability of saying 1 when predictor is 0), which we take as our criterion  $c$ . The slope of the model ( $\beta_1$ ) is the increased probability of responding “match” when the trial



type is “match,” in  $z$ -scores, which is another expression of  $d'$ . Therefore,  $c = -zHR = -\beta_0$ , and  $d' = \beta_1$ .

In our experimental design, there are three conditions for both match and non-match trials, we can estimate the  $d'$  and  $c$  separately for each condition. In this case, the criterion  $c$  is modeled as the main effect of valence, and the  $d'$  can be modeled as the interaction between valence and match:

$$\Phi(p_i) = 0 + \beta_0 Valence_i + \beta_1 IsMatch_i * Valence_i$$

In each experiment, we had multiple participants. We can estimate the group-level parameters by extending the above model into a two-level model, where we can estimate parameters on individual level (varying effect) and the group level parameter simultaneously (fixed effect). The probability that the  $j$ th subject responded “match” ( $y_{ij} = 1$ ) at the  $i$ th trial  $p_{ij}$ . In the same vein, we have

$$y_{ij} \sim Bernoulli(p_{ij})$$

The the generalized linear model can be re-written to include two levels:

$$\Phi(p_{ij}) = 0 + \beta_{0j} Valence_{ij} + \beta_{1j} IsMatch_{ij} * Valence_{ij}$$

We again can write the generalized linear model on the probits ( $z$ -scores;  $\Phi$ , “Phi”) of  $ps$ .

The subjective-specific intercepts ( $\beta_0 = -zFAR$ ) and slopes ( $\beta_1 = d'$ ) are describe by multivariate normal with means and a covariance matrix for the parameters.

$$\begin{bmatrix} \beta_{0j} \\ \beta_{1j} \end{bmatrix} \sim N\left(\begin{bmatrix} \theta_0 \\ \theta_1 \end{bmatrix}, \Sigma\right)$$

For experiments that had 2 (matching: match vs. non-match) by 3 (moral character: good vs. neutral vs. bad), i.e., experiment 1a, 1b, 1c, 2, 5, and 6a, the formula for accuracy in BRMs is as follow:

```

425     saymatch ~ 0 + Valence + Valence:ismatch + (0 + Valence +
426 Valence:ismatch | Subject), family = bernoulli(link="probit")

```

427 For experiments that had two by two by three design, we used the follow formula for  
 428 the BGLM:

```

429     saymatch ~ 0 + ID:Valence + ID:Valence:ismatch + (0 + ID:Valence +
430 ID:Valence:ismatch | Subject), family = bernoulli(link="probit")

```

431 In the same vein, we can estimate the posterior of parameters across different  
 432 experiments. We can use a nested hierarchical model to model all the experiment with  
 433 similar design:

$$y_{ijk} \sim \text{Bernoulli}(p_{ijk})$$

434 the generalized linear model is then

$$\Phi(p_{ijk}) = 0 + \beta_{0jk} \text{Valence}_{ijk} + \beta_{1j} \text{IsMatch}_{ijk} * \text{Valence}_{ijk}$$

435 The outcomes  $y_{ijk}$  are 0 if participant  $j$  in experiment  $k$  responded “nonmatch” on trial  $i$ ,  
 436 1 if they responded “match.”

$$\begin{bmatrix} \beta_{0jk} \\ \beta_{1jk} \end{bmatrix} \sim N\left(\begin{bmatrix} \theta_{0k} \\ \theta_{1k} \end{bmatrix}, \Sigma\right)$$

437 and the experiment level parameter  $mu_{0k}$  and  $mu_{1k}$  is from a higher order  
 438 distribution:

$$\begin{bmatrix} \theta_{0k} \\ \theta_{1k} \end{bmatrix} \sim N\left(\begin{bmatrix} \mu_0 \\ \mu_1 \end{bmatrix}, \Sigma\right)$$

439 in which  $mu_0$  and  $mu_1$  means the population level parameter.

440 *Reaction times.* For the reaction time, we used the log normal distribution  
 441 ([https://lindeloev.github.io/shiny-rt/#34\\_\(shifted\)\\_log-normal](https://lindeloev.github.io/shiny-rt/#34_(shifted)_log-normal)) to model the data. This

means that we need to estimate the posterior of two parameters:  $\mu$ ,  $\sigma$ .  $\mu$  is the mean of the `logNormal` distribution, and  $\sigma$  is the disperse of the distribution. Although the log normal distribution can be extended to shifted log normal distribution, with one more parameter: shift, which is the earliest possible response, we found that the additional parameter didnt' improved the model fitting and therefore used the `logNormal` in our final analysis.

The reaction time of the  $j$ th subject on  $i$ th trial is a linear function of trial type:

$$y_{ij} = \beta_{0j} + \beta_{1j} * IsMatch_{ij} * Valence_{ij}$$

while the log of the reaction time is log-normal distributed:

$$\log(y_{ij}) \sim N(\mu_j, \sigma_j)$$

$y_{ij}$  is the RT of the  $i$ th trial of the  $j$ th participants.

$$\mu_j \sim N(\mu, \sigma)$$

$$\sigma_j \sim Cauchy()$$

Formula used for modeling the data as follow:

```
RT_sec ~ Valence*ismatch + (Valence*ismatch | Subject), family =  
lognormal()
```

or

```
RT_sec ~ ID*Valence*ismatch + (ID*Valence*ismatch | Subject), family =  
lognormal()
```

we expanded the RT model three-level model in which participants and experiments are two group level variable and participants were nested in the experiments.

$$\log(y_{ijk}) \sim N(\mu_{jk}, \sigma_{jk})$$

$y_{ijk}$  is the RT of the  $i$ th trial of the  $j$ th participants in the  $k$ th experiment.

$$\mu_{jk} \sim N(\mu_k, \sigma_k)$$

$$\sigma_{jk} \sim \text{Cauchy}()$$

$$\mu_k \sim N(\mu, \sigma)$$

$$\theta_k \sim \text{Cauchy}()$$

**Effect of moral character.** We estimated the effect size of  $d'$  and RT from experiment 1a, 1b, 1c, 2, 5, and 6a for the effect of moral character. We reported fixed effect of three-level BHM that included all experiments that tested the valence effect.

**Interaction between moral character and self-referential process.** We also estimated the interaction between moral character and self-referential process, which included results from experiment 3a, 3b, and 6b. Using three-level models, we tested two possible explanations for the prioritization of good character: value-based or social categorization based prioritization.

**Implicit interaction between valence and self-relevance.** In the third part, we focused on experiment 4a and 4b, which were designed to examine two more nuanced explanation concerning the good-self. The design of experiment 4a and 4b are complementary. Together, they can test whether participants are more sensitive to the moral character of the Self (4a), or the identity of the good character (4b).

For the questionnaire part, we are most interested in the self-rated distance between different person and self-evaluation related questionnaires: self-esteem, moral-self identity, and moral self-image. Other questionnaires (e.g., personality) were not planned to

correlated with behavioral data were not included. Note that all questionnaire data were reported in (Liu et al., 2020).

## Results

### Perceptual processing moral character related information

In this part, we report results from five experiments that tested whether an associative learning task, including 192 participants. Note that for both experiment 1a and 1b, there were two independent samples with different equipment, trials numbers and testing situations. Therefore, we modeled them as independent samples. These five experiments revealed a robust effect of moral character on perceptual matching task.

For the  $d$  prime, we found robust effect of moral character. Shapes associated with good character (“good person,” “kind person” or a name associated with morally good behavioral history) has higher sensitivity (median = 2.49, 95% HDI = [2.19 2.75]) than shapes associated with neutral character (median = 2.18, 95% HDI = [1.90 2.48]),  $median_{diff} = 0.31$ , 95% HDI [0.02 0.63], but we did not find differences between shapes associated with bad character (median = 2.23, 95% HDI = [1.94 2.53]) and neutral character,  $median_{diff} = 0.05$ , 95% HDI [-0.29 0.37].

For the reaction times, we also found robust effect of moral character for both match trials (see figure 1 C) and nonmatch trials (**see supplementary materials**). For match trials, shapes associated with good character has faster responses (median = 578.64 ms, 95% HDI = [508.15 661.14]) than shapes associated with neutral character (median = 623.45 ms, 95% HDI = [547.98 708.24]),  $median_{diff} = -44.05$ , 95% HDI [-59.96 -30.43]. We also found that the responses to shapes associated with bad character (median = 640.41 ms, 95% HDI = [559.94 719.63]) were slower as compared to the neutral character,  $median_{diff} = 17.04$ , 95% HDI [4.02 29.92]. See Figure 1.

For the nonmatch trials, we also found the advantage of good character: Shapes

associated with good character (median = 653.21 ms, 95% HDI = [574.65 739.57]) are faster than shapes associated with neutral (median = 671.14 ms, 95% HDI = [591.71 760.09]),  $median_{diff} = -17.65$  ms, 95% HDI [-23.85 -10.36]. Similarly, the shapes associated with bad character (median = 676.35 ms, 95% HDI = [599.13 767.76]) was responded slower than shapes associated with neutral character,  $median_{diff} = 17.04$  ms, 95% HDI [4.02 29.92], but the effect size was smaller, (see **supplementary materials**).

### Self-referential process modulate prioritization of good character

In this part, we report results from three experiments (3a, 3b, and 6b) that aimed at testing whether the moral valence effect found in the previous experiments is modulated by self-referential processes. These three experiments included data from 108 participants.

Because we have found that a facilitation effect of good character and slow-down effect of bad character in the first part, in this part, we will focus on the whether such effect interact with self-referential factor. In others words, we not only reported differences between good/bad character with neutral character for self-referential and other-referential separately, but also compare the differences between the difference.

For the  $d$  prime, we found that an interaction between moral character effect and self-referential, the self- and other-referential difference was greater than zero for good vs. neutral character differences ( $median_{diff} = 0.51$ ; 95% HDI = [-1.48 2.61]) but not for bad vs. neutral differences ( $median_{diff} = -0.02$ ; 95% HDI = [-1.85 2.17]). Further analyses revealed that the good vs. neutral character effect only appeared for self-referential conditions but not other-referential conditions. The estimated  $d$  prime for good-self was greater than neutral-self ( $median_{diff} = 0.56$ ; 95% HDI = [-1.05 2.15]),  $d$  prime for good-self was also greater than good-other condition ( $median_{diff} = ;$  95% HDI = [ ]). The differences between bad-self and neutral-self, good-other and neutral-other, bad-other and neutral-other are all centered around zero (see Figure 2, B, D).

For the RTs part, we also found the interaction between moral character and self-referential, the self- and other-referential differences was below zero for the good vs. neutral differences ( $median_{diff} = -110.23$ ; 95% HDI =  $[-587.40 \ 307.33]$ ) but not for the bad vs. neutral differences ( $median_{diff} = -14.83$ ; 95% HDI =  $[-235.54 \ 138.36]$ ). Further analyses revealed a robust good-self prioritization effect as compared to neutral-self ( $median_{diff} = -51.73$ ; 95% HDI =  $[-144.56 \ 1.59]$ ) and good-other ( $median_{diff} = -51.69$ ; 95% HDI =  $[-818.62 \ 743.60]$ ) conditions. Also, we found that both good character and bad character were responded slower than neutral character when it was other-referential. See Figure 2.

### Binding the good and self

In this part, we reported two studies in which the moral valence or the self-referential processing is not task-relevant. We are interested in testing whether the task-relevance modulated the effect observed in previous experiment.

For the task relevant part, we found self-related conditions were performed better than other-related conditions, on both  $d$  prime and reaction times.

Most importantly, we found evidence, albeit weak, that task-irrelevant moral valence also played an role. The  $d$  prime is greater when shapes were associated with good self condition than with neutral self ( $BF = 4.4$ ) or bad self (3.1), but shapes associated with bad self and neutral self didn't show differences. In contrast the  $d$  prime was smaller when shapes were associated with good other than with neutral other or bad other. See Figure 3.

The same pattern was found for RTs. For self-referential condition, when good character was presented as a task-irrelevant stimuli, the responds were facilitated. This effect was reversed for other-referential condition.

In this task, we found shapes associated with good person conditions were performed better than other-related conditions, on both  $d$  prime and reaction times.

Most importantly, we found evidence, that task-irrelevant self-relevance also played an role. For shapes associated with good person, the  $d$  prime was greater when shapes had an “self” inside as task-irrelevant stimuli than with “other” inside ( $mean_{diff} = 0.14$ , 95% credible intervals  $[-0.02, 0.31]$ ,  $BF = 12.07$ ,  $p = 0.92$ ), but this effect did not happen when the target shape where associated with “neutral” ( $mean_{diff} = 0.04$ , 95% CI  $[-.11, .18]$ ) or “bad” person ( $mean_{diff} = -.05$ , 95% CI  $[-.18, .09]$ ). The same trend appear for the RT data. For shapes associated with good person, an “self” inside will reduce the RTs as compared with when a “other” inside the shape ( $mean_{diff} = -55$  ms, 95%CI  $[-75, -35]$ ,  $p < 0.0001$ ), but this effect did not occur when the shapes were associated neutral ( $mean_{diff} = 10$ , 95% CI  $[1, 20]$ ) or bad ( $mean_{diff} = 5$ , 95%CI  $[-16, 27]$ ) person. See Figure 3.

### Self-reported personal distance

See Figure ??.

### Correlation analyses

The reliability of questionnaires can be found in (Liu et al., 2020). We calculated the correlation between the data from behavioral task and the questionnaire data. First, we calculated the score for each scale based on their structure and factor loading, instead of sum score (McNeish & Wolf, 2020). Then, we used SEM to estimate the correlation because it can include measurement model and statistical model in a unified framework.

To make sure that what we found were not false positive, we used two method to ensure the robustness of our analysis. first, we split the data into two half: the data with self and without, then, we used the conditional random forest to find the robust correlation in the exploratory data (with self reference) that can be replicated in the confirmatory data (without the self reference). The robust correlation were then analyzed using SEM

Instead of use the exploratory correlation analysis, we used a more principled way to



explore the correlation between parameter of HDDM ( $v$ ,  $t$ , and  $a$ ) and scale scores and person distance.

We didn't find the correlation between scale scores and the parameters of HDDM, but found weak correlation between personal distance and the parameter estimated from Good and neutral conditions.

First, boundary separation ( $a$ ) of moral good condition was correlated with both Self-Bad distance ( $r = 0.198$ , 95% CI  $[-0.05, 0.45]$ ,  $p = 0.0063$ ) and Neutral-Bad distance ( $r = 0.1571$ , 95% CI  $[-0.05, 0.36]$ ,  $p = 0.031$ ). At the same time, the non-decision time is negatively correlated with Self-Bad distance ( $r = 0.169$ , 95% CI  $[-0.05, 0.39]$ ,  $p = 0.0197$ ). See Figure ??.

Second, we found the boundary separation of neutral condition is positively correlated with the personal distance between self and good distance ( $r = 0.189$ , 95% CI  $[-0.05, 0.43]$ ,  $p = 0.036$ ), but negatively correlated with self-neutral distance ( $r = -0.183$ , 95% CI  $[-0.43, -0.03]$ ,  $p = 0.042$ ). Also, the drift rate of the neutral condition is positively correlated with the Self-Bad distance ( $r = 0.177$ , 95% CI  $[-0.05, 0.40]$ ,  $p = 0.048$ ).a. See figure ??

We also explored the correlation between behavioral data and questionnaire scores separately for experiments with and without self-referential, however, the sample size is very low for some conditions.

## Discussion

In a series of experiments, we found that (1) good character are prioritized in perceptual matching task; (2) this effect was robust when moral characters are self-referential but not stranger-referential; (3) the self-good character combination, whether task-relevant or not, facilitate the process but other-good character combination didn't have this effect, if not reverse. The self-reported mental distance scale also showed that people rated self has longer distance to bad character.

[direct evidence for moral character in perception]

[Value-based attention?]

[Good-self effect]

## References

- Abele, A. E., Ellemers, N., Fiske, S. T., Koch, A., & Yzerbyt, V. (2020). Navigating the social world: Toward an integrated framework for evaluating self, individuals, and groups. *Psychological Review*. <https://doi.org/10.1037/rev0000262>
- Abele, A. E., & Wojciszke, B. (2007). Agency and communion from the perspective of self versus others. *Journal of Personality and Social Psychology*, *93*(5), 751–763. <https://doi.org/10.1037/0022-3514.93.5.751>
- Anderson, Brian A. (2019). Neurobiology of value-driven attention. *Current Opinion in Psychology*, *29*, 27–33. <https://doi.org/10.1016/j.copsyc.2018.11.004>
- Anderson, Brian A., Laurent, P. A., & Yantis, S. (2011). Value-driven attentional capture. *Proceedings of the National Academy of Sciences*, *108*(25), 10367–10371. <https://doi.org/10.1073/pnas.1104047108>
- Anderson, E., Siegel, E. H., Bliss-Moreau, E., & Barrett, L. F. (2011). The visual impact of gossip. *Science*, *332*(6036), 1446–1448. <https://doi.org/10.1126/science.1201574>
- Baumeister, R. F., Bratslavsky, E., Finkenauer, C., & Vohs, K. D. (2001). Bad is stronger than good. *Review of General Psychology*, *5*(4), 323–370. <https://doi.org/10.1037/1089-2680.5.4.323>
- Baumeister, R. F., Bratslavsky, E., Finkenauer, C., & Vohs, K. D. (2001). Bad is stronger than good. *Review of General Psychology*, *5*(4), 323–370. <https://doi.org/10.1037/1089-2680.5.4.323>

- Bliss-Moreau, E., Barrett, L. F., & Wright, C. I. (2008). Individual differences in learning the affective value of others under minimal conditions. *Emotion*, 8(4), 479–493. <https://doi.org/10.1037/1528-3542.8.4.479>
- Bürkner, P.-C. (2017). Brms: An r package for bayesian multilevel models using stan [Journal Article]. *Journal of Statistical Software; Vol 1, Issue 1 (2017)*. Retrieved from <https://www.jstatsoft.org/v080/i01%20http://dx.doi.org/10.18637/jss.v080.i01>
- Carpenter, B., Gelman, A., Hoffman, M. D., Lee, D., Goodrich, B., Betancourt, M., ... Riddell, A. (2017). Stan: A probabilistic programming language [Journal Article]. *Journal of Statistical Software*, 76(1). <https://doi.org/10.18637/jss.v076.i01>
- Cushman, F., Young, L., & Hauser, M. (2006). The role of conscious reasoning and intuition in moral judgment: Testing three principles of harm. *Psychological Science*, 17(12), 1082–1089. <https://doi.org/10.1111/j.1467-9280.2006.01834.x>
- Dang, J., King, K. M., & Inzlicht, M. (2020). Why are self-report and behavioral measures weakly correlated? *Trends in Cognitive Sciences*, 24(4), 267–269. <https://doi.org/10.1016/j.tics.2020.01.007>
- DeScioli, P. (2016). The side-taking hypothesis for moral judgment. *Current Opinion in Psychology*, 7, 23–27. <https://doi.org/10.1016/j.copsyc.2015.07.002>
- Dunbar, R. I. M. (2004). Gossip in evolutionary perspective. *Review of General Psychology*, 8(2), 100–110. <https://doi.org/10.1037/1089-2680.8.2.100>
- Eiserbeck, A., & Abdel Rahman, R. (2020). Visual consciousness of faces in the attentional blink: Knowledge-based effects of trustworthiness dominate over appearance-based impressions. *Consciousness and Cognition*, 83, 102977. <https://doi.org/10.1016/j.concog.2020.102977>

Ellemers, N. (2018). Morality and social identity. In M. van Zomeren & J. F. Dovidio (Eds.), *The oxford handbook of the human essence* (pp. 147–158). New York, NY, US: Oxford University Press.

Enock, F. E., Hewstone, M. R. C., Lockwood, P. L., & Sui, J. (2020). Overlap in processing advantages for minimal ingroups and the self. *Scientific Reports*, 10(1), 18933. <https://doi.org/10.1038/s41598-020-76001-9>

Falvello, V., Vinson, M., Ferrari, C., & Todorov, A. (2015). The robustness of learning about the trustworthiness of other people. *Social Cognition*, 33(5), 368–386. <https://doi.org/10.1521/soco.2015.33.5.368>

Fiske, S. (1980). Attention and weight in person perception: The impact of negative and extreme behavior. *Journal of Personality and Social Psychology*, 38(6), 889–906. Retrieved from [insights.ovid.com](https://insights.ovid.com)

Freeman, J. B., & Ambady, N. (2011). A dynamic interactive theory of person construal. *Psychological Review*, 118(2), 247–279. <https://doi.org/10.1037/a0022327>

Goh, J. X., Hall, J. A., & Rosenthal, R. (2016). Mini meta-analysis of your own studies: Some arguments on why and a primer on how [Journal Article]. *Social and Personality Psychology Compass*, 10(10), 535–549. <https://doi.org/10.1111/spc3.12267>

Goodwin, G. P. (2015). Moral character in person perception. *Current Directions in Psychological Science*, 24(1), 38–44. <https://doi.org/10.1177/0963721414550709>

Goodwin, G. P., Piazza, J., & Rozin, P. (2014). Moral character predominates in person perception and evaluation. *Journal of Personality and Social Psychology*, 106(1), 148–168. <https://doi.org/10.1037/a0034726>

- Haidt, J. (2007). The new synthesis in moral psychology. *Science*, 316(5827), 998–1002. <https://doi.org/10.1126/science.1137651>
- Hofmann, W., Wisneski, D. C., Brandt, M. J., & Skitka, L. J. (2014). Morality in everyday life. *Science*, 345(6202), 1340–1343. <https://doi.org/10.1126/science.1251560>
- Hu, C.-P., Lan, Y., Macrae, C. N., & Sui, J. (2020). Good me bad me: Does valence influence self-prioritization during perceptual decision-making? [Journal Article]. *Collabra: Psychology*, 6(1), 20. <https://doi.org/10.1525/collabra.301>
- Liu, Q., Wang, F., Yan, W., Peng, K., Sui, J., & Hu, C.-P. (2020). Questionnaire data from the revision of a chinese version of free will and determinism plus scale [Journal Article]. *Journal of Open Psychology Data*, 8(1), 1. <https://doi.org/10.5334/jopd.49/>
- McHugh, C., McGann, M., Igou, E. R., & Kinsella, E. (2019). *Moral judgment as categorization (MJAC)*. PsyArXiv. <https://doi.org/10.31234/osf.io/72dzp>
- McNeish, D., & Wolf, M. G. (2020). Thinking twice about sum scores. *Behavior Research Methods*. <https://doi.org/10.3758/s13428-020-01398-0>
- Ohman, A., Lundqvist, D., & Esteves, F. (2001). The face in the crowd revisited: A threat advantage with schematic stimuli. *Journal of Personality and Social Psychology*, 80(3), 381–396. <https://doi.org/10.1037/0022-3514.80.3.381>
- Pool, E., Brosch, T., Delplanque, S., & Sander, D. (2016). Attentional bias for positive emotional stimuli: A meta-analytic investigation. *Psychological Bulletin*, 142(1), 79–106. <https://doi.org/10.1037/bul0000026>
- Pratto, F., & John, O. P. (1991). Automatic vigilance: The attention-grabbing power of negative social information. *Journal of Personality and Social Psychology*, 61(3), 380–391. <https://doi.org/10.1037//0022-3514.61.3.380>

- Rai, T. S., & Fiske, A. P. (2011). Moral psychology is relationship regulation: Moral motives for unity, hierarchy, equality, and proportionality. *Psychological Review*, 118(1), 57–75. <https://doi.org/10.1037/a0021867>
- Rouder, J. N., & Lu, J. (2005). An introduction to bayesian hierarchical models with an application in the theory of signal detection [Journal Article]. *Psychonomic Bulletin & Review*, 12(4), 573–604. <https://doi.org/10.3758/bf03196750>
- Rousselet, G. A., & Wilcox, R. R. (2019). Reaction times and other skewed distributions: Problems with the mean and the median [Preprint]. *Meta-Psychology*. <https://doi.org/10.1101/383935>
- Schupp, H. T., Ohman, A., Junghöfer, M., Weike, A. I., Stockburger, J., & Hamm, A. O. (2004). The facilitated processing of threatening faces: An ERP analysis. *Emotion (Washington, D.C.)*, 4(2), 189–200. <https://doi.org/10.1037/1528-3542.4.2.189>
- Shore, D. M., & Heerey, E. A. (2013). Do social utility judgments influence attentional processing? *Cognition*, 129(1), 114–122. <https://doi.org/10.1016/j.cognition.2013.06.011>
- Siegel, J. Z., Mathys, C., Rutledge, R. B., & Crockett, M. J. (2018). Beliefs about bad people are volatile. *Nature Human Behaviour*, 2(10), 750–756. <https://doi.org/10.1038/s41562-018-0425-1>
- Simmons, J. P., Nelson, L. D., & Simonsohn, U. (2013). *Life after p-hacking* [Conference Proceedings]. <https://doi.org/10.2139/ssrn.2205186>
- Skowronski, J. J., & Carlston, D. E. (1989). Negativity and extremity biases in impression formation: A review of explanations. *Psychological Bulletin*, 105(1), 131–142. <https://doi.org/10.1037/0033-2909.105.1.131>

- Stein, T., Grubb, C., Bertrand, M., Suh, S. M., & Verosky, S. C. (2017). No impact of affective person knowledge on visual awareness: Evidence from binocular rivalry and continuous flash suppression. *Emotion*, 17(8), 1199–1207. <https://doi.org/10.1037/emo0000305>
- Strohminger, N., Knobe, J., & Newman, G. (2017). The true self: A psychological concept distinct from the self: *Perspectives on Psychological Science*. <https://doi.org/10.1177/1745691616689495>
- Sui, J., He, X., & Humphreys, G. W. (2012). Perceptual effects of social salience: Evidence from self-prioritization effects on perceptual matching [Journal Article]. *Journal of Experimental Psychology: Human Perception and Performance*, 38(5), 1105–1117. <https://doi.org/10.1037/a0029792>
- Todorov, A., & Olson, I. R. (2008). Robust learning of affective trait associations with faces when the hippocampus is damaged, but not when the amygdala and temporal pole are damaged. *Social Cognitive and Affective Neuroscience*, 3(3), 195–203. <https://doi.org/10.1093/scan/nsn013>
- Turner, J. C., Hogg, M. A., Oakes, P. J., Reicher, S. D., & Wetherell, M. S. (1987). *Rediscovering the social group: A self-categorization theory*. Cambridge, MA, US: Basil Blackwell.
- Uhlmann, E. L., Pizarro, D. A., & Diermeier, D. (2015). A person-centered approach to moral judgment: *Perspectives on Psychological Science*. <https://doi.org/10.1177/1745691614556679>
- Vanneste, S., Verplaetse, J., Van Hiel, A., & Braeckman, J. (2007). Attention bias toward noncooperative people. A dot probe classification study in cheating detection. *Evolution and Human Behavior*, 28(4), 272–276. <https://doi.org/10.1016/j.evolhumbehav.2007.02.005>

- 749 Xiao, Y. J., Coppin, G., & Bavel, J. J. V. (2016). Perceiving the world through  
750 group-colored glasses: A perceptual model of intergroup relations. *Psychological*  
751 *Inquiry*, 27(4), 255–274. <https://doi.org/10.1080/1047840X.2016.1199221>
- 752 Young, L., Cushman, F., Hauser, M., & Saxe, R. (2007). The neural basis of the  
753 interaction between theory of mind and moral judgment. *Proceedings of the*  
754 *National Academy of Sciences*, 104(20), 8235–8240.  
755 <https://doi.org/10.1073/pnas.0701408104>



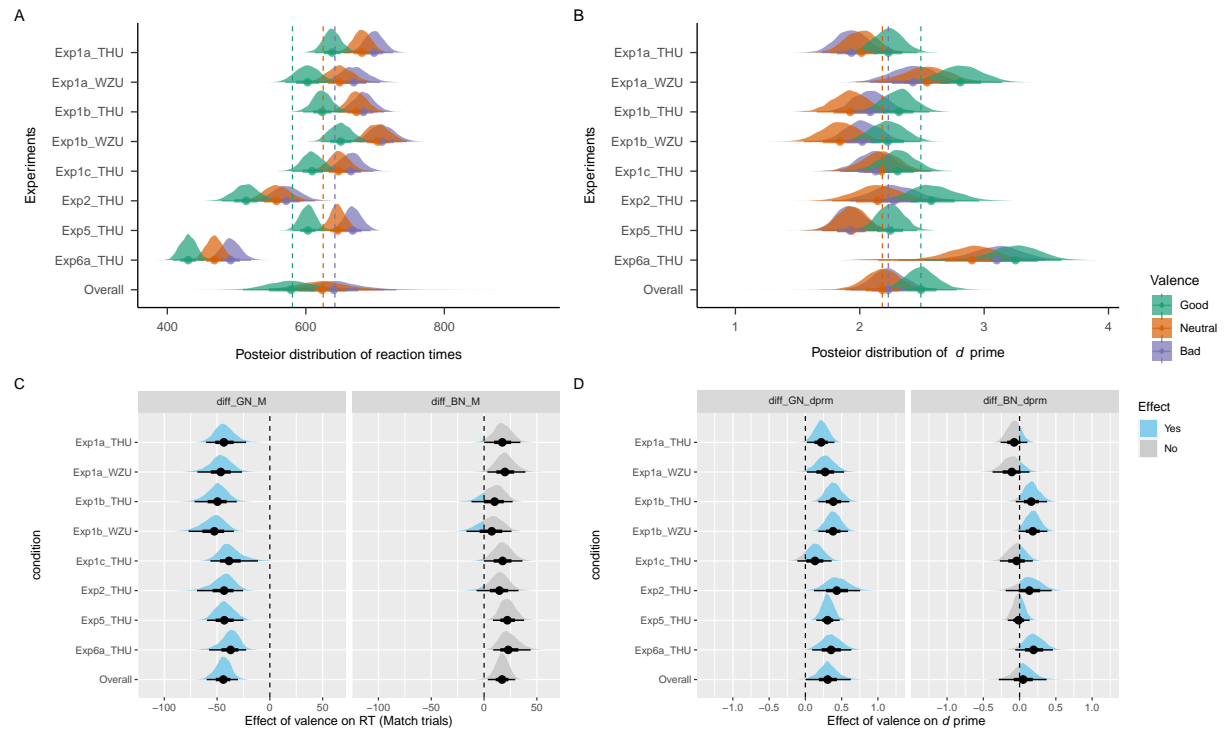


Figure 1. Effect of moral valence on RT and  $d'$

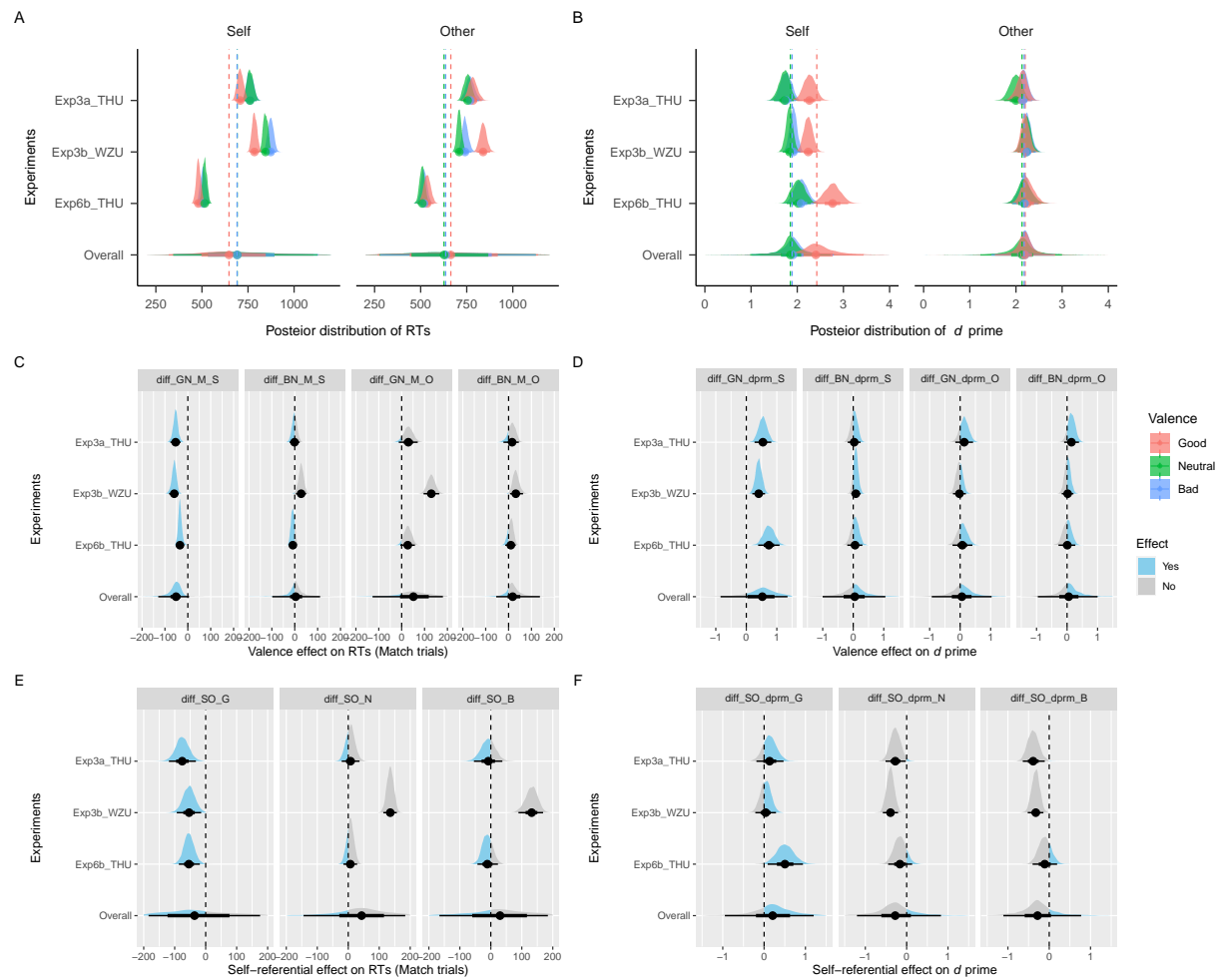


Figure 2. Interaction between moral valence and self-referential

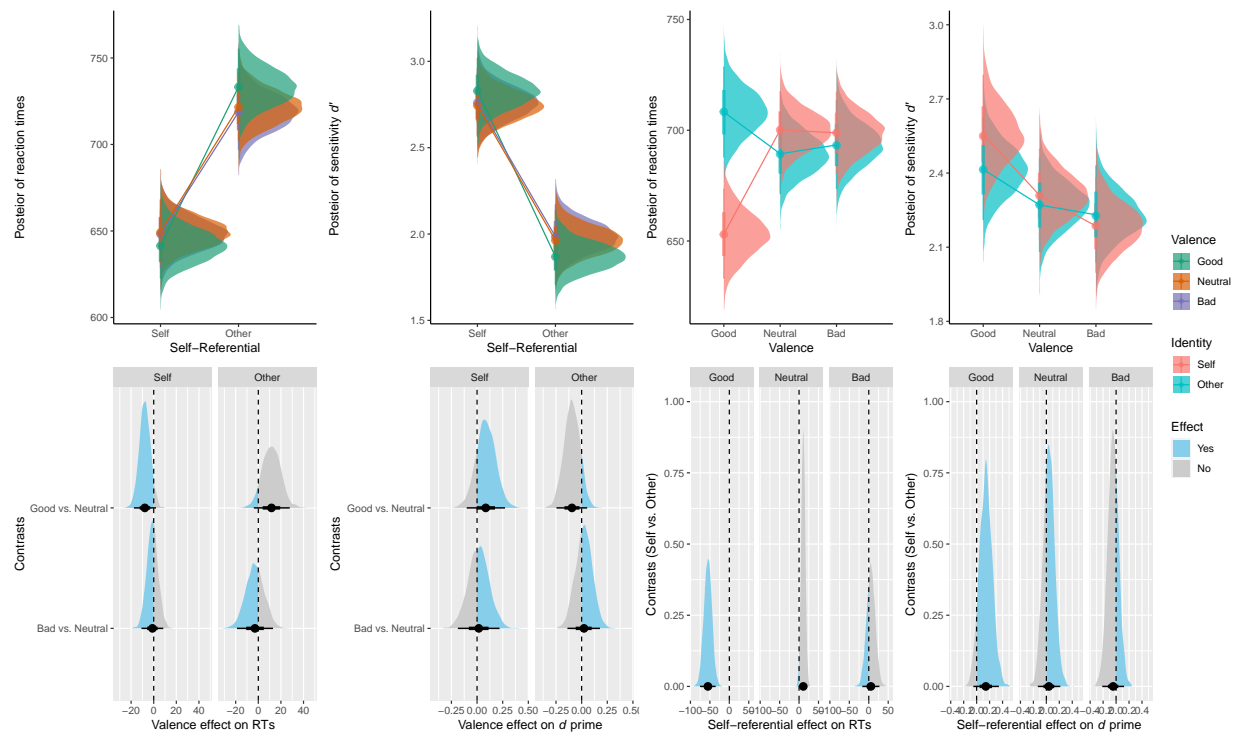


Figure 3. exp4: Results of Bayesian GLM analysis.